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Outside Job Opportunities and the Gender Gap in Pay *

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Abstract

We show that the wages of men and women are differentially affected by outside options, and that these differential responses contribute to the gender pay gap. We develop a simple model of on-the-job search that integrates two crucial gender differences: job preferences and the propensity to renegotiate wages in response to external offers. Both factors contribute to lower wage responsiveness for women when they receive outside offers, and a negative female-male pay gap. However, women's job mobility responses vary depending on the underlying mechanism. To empirically test our model's predictions, we analyze wage and job mobility responses of men and women to external job opportunities, mediated through family networks. Using Swedish register data, we find that improved outside options are associated with higher within-job wage growth for men but not for women. Importantly, we can rule out that these gendered responses arise from differences in the quality of external offers as these are balanced across genders by design. Additionally, men's and women's job mobility responses are very similar. In the light of the model, we attribute these findings to differences in negotiation behavior between men and women. Policies encouraging women to bargain in response to outside options may thus be a powerful tool for reducing the remaining within-job gender gap in pay.

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1 Introduction

The gender pay gap is pervasive, also within occupation and within firm. Strikingly, women receive lower pay than their male colleagues, even when they hold identical positions within firm (Card et al. 2016, Illing et al. 2023). Recent studies indicate that systematic differences in outside options (Caldwell and Danieli 2024) and wage negotiation behavior between men and women contribute significantly to the gender pay gap (Biasi and Sarsons 2022, Caldwell et al. 2024, Roussille 2024). In this paper we ask whether (and why) differential wage responsiveness to outside offers contributes to the gender wage gap within job.

Addressing this question requires us to tackle a number of empirical challenges. First, information on outside job offers is rarely available in representative samples of men and women. Second, individual differences in the number of outside offers are likely confounded by variation in individual productivity. Third, it is likely that the attractiveness of a given offer differs systematically across the genders. Our empirical strategy—outlined below—addresses all of these challenges.

To shed light on the mechanisms driving the relationship between outside offers and the within-job gender wage gap, we first outline a simple theoretical model. Following Postel-Vinay and Robin (2002) and Cahuc et al. (2006), workers can use outside offers to negotiate higher wages. We consider two key differences between men and women: (i) their job preferences, as captured by their willingness to commute, and (ii) their costs of wage renegotiation. Both mechanisms lower women's share of match-specific rents. However, an improvement in outside options has an ambiguous impact on the gender differential in job-to-job mobility. Specifically, a lower arrival rate of relevant job offers *reduces* female job mobility, while higher bargaining costs *increase* mobility, as women tend to move at higher rates when they do not renegotiate with their current employers.

To test the model predictions we use information on family networks (siblings and parents), in combination with labor demand changes in connected firms, to quantify wage and job mobility responses among women and men to changes in outside options. Our research design builds on the idea that social connections are fundamental mediators of job opportunities, a phenomenon well-documented across various countries, settings, and types of connections.[1]

We focus on family links for substantive and methodological reasons. Substantively, family links are central mediators of information on job opportunities. For instance, Eliason et al. (2023) show that displaced workers are four times more likely to find re-employment in firms where a family member is employed, compared to a former co-worker, and ten times more likely compared to a former classmate or neighbor.[2] The significant role of strong ties in the job search process suggests that the interaction between labor demand changes in firms and social connections can provide variation in (information about) job opportunities across otherwise

[1] There is by now a large literature which uses register data to investigate the role of different kinds of networks in the job search process, see, e.g., Bayer et al. (2008); Hellerstein et al. (2011) and Schmutte (2015) for the role of neighbors, Cingano and Rosolia (2012), Hensvik and Skans (2016) and Glitz (2017) for the role of co-workers, Dustmann et al. (2015) for the role of ethnic networks, Kramarz and Skans (2014) for the role of parents and Eliason et al. (2023) for the role of all of the above.

[2] Using Facebook data on job seeker's social networks, Gee et al. (2017a) and Gee et al. (2017b) present evidence suggesting that strong ties are more valuable than weak ties in generating information about job opportunities.

similar workers and over time. Methodologically, the quality of family networks is likely balanced across the genders. This is in sharp contrast to other conceivable network definitions, such as those based on former coworkers or schoolmates, where differential selection across the genders will cause the characteristics of the networks to differ. Using family networks, we thus obtain quasi-experimental variation in the access to information about external job opportunities of similar quality across the genders.

Our setting is Sweden, a country known for its high gender equality and compressed wage structure. But despite these features, we document a substantial gender gap in hourly wages, particularly among private sector white-collar workers. Women earn 14 percent less than men when controlling for age and education, and 8.6 percent less within the same job (establishment $\times$ 3-digit occupation).[3] A salient feature is that the within-job gender wage gap grows with firm tenure.

We estimate the impact of the arrival of outside job opportunities on the within match wage growth of men and women. Our primary focus is on white-collar workers in the private sector, as wages are more flexible for this group.[4] To enhance the relevance of potential job offers, we focus on occupation-specific demand changes in connected establishments. Since the quality of family networks is balanced across the genders, the estimates are robust to including a range of fixed effects. Adding worker-by-plant, plant-by-time, occupation-by-time, and age fixed effects does not change the key estimates of interest.

Our empirical strategy is similar in spirit to Caldwell and Harmon (2019) who show that wages and job mobility respond positively to (information about) outside job offers arising through professional networks in Denmark. In relation to their paper we focus on the role of outside options as a source of gender pay inequality. For this purpose, we exploit job offers via family, rather than professional contacts. This is an important difference since the quality of offers via professional ties varies systematically across genders (reflecting gender labor market segregation). In contrast, job opportunities mediated by family contacts are balanced across genders (as we show in the sequel).

Despite outside job opportunities being, on average, the same for men and women, the wage responses differ: men experience a wage gain within their current match, while women's wages are unaffected. Consequently, the arrival of outside job opportunities widens the gender wage gap.

In terms of magnitudes, our baseline estimates suggest that a job opening within the family network has a relatively small—but precisely estimated—impact on the gender pay gap. However, it is essential to take into account that only a subset of job offers are relevant for renegotiation.[5] To address this issue, we construct a measure of the share of viable offers by predicting the fraction of job openings that should lead to renegotiation based on the theory. According to this exercise, about 30% of the openings are relevant for renegotiation. When we adjust our estimates for the fraction of offers that are relevant, we can explain about half of the

[3]We describe the institutional features in Section 3. While collective agreements stipulate the terms for wage setting, there is still scope for individual employer-employee wage bargaining.

[4]We show in Section 4 that the gender wage gap is substantially larger in this segment of the labor market.

[5]Whether the offer is relevant or not depends on whether the outside firm can pay the worker in excess of the current wage (see discussion in Section 2).

within-spell growth rate in the gender gap. Note, however, that there are reasons to expect that our estimates provide a lower-bound on the true impact of outside options: in the register data, we do not know whether the worker had information about the job opportunity and whether the worker received the offer.

We conduct a series of robustness checks to address concerns related to gender-based sorting across jobs, the measurement of outside opportunities, and sample restrictions. Overall, our findings are very robust to these alterations. Additionally, we show that wages for workers exposed to network-based job opportunities follow a parallel trend to those of unexposed workers in the years leading up to the new opportunity, but diverge in the year of exposure.

To shed light on the mechanisms, we provide two important pieces of evidence. First, we document the impact on job mobility. In contrast to the wage response, we find a similar impact on job-to-job mobility in response to network job openings for men and women: in years when a connected plant is hiring, the probability of moving to that plant increases more than fourfold (from a low baseline probability). Interpreted through the lens of our model, these estimates suggest that the network job opportunities are known and valued by both men and women, but only used by males to bid up wages in current jobs.

Second, we complement our analysis of white collar workers with results for blue-collar workers, a group with very limited scope for individual wage negotiation. In line with the notion of constrained bargaining, we do not find a wage response to outside options for any of the genders while the mobility response is still substantial (for both genders). These results are consistent with limited opportunities for renegotiation. Moreover, they suggest that the design of collective agreements can influence the gender pay gap.

In terms of heterogeneity, we differentiate between job opportunities by sector, location and AKM firm wage effects. Our results suggest that male workers bid up their wage in response to a broad set of job opportunities. While those emerging at other private sector firms generate larger effects, the geographical location of the job or the wage premium of the expanding plant appear to be less important. In contrast, women do not experience a wage increase in response to any type of job offer (private or public; high or low productivity; close or far away).

The mobility response, however, is influenced by the quality and location of the expanding plant for both genders. As predicted by the theory, workers of both genders are 4-5 times more likely to move into connected plants if they have a higher wage premium (as measured by job Abowd et al. 1999 fixed effects) compared to the current plant. The mobility response is negatively related to commuting time for both genders, suggesting that both men and women find jobs with a longer commute less relevant. Notably, the destination firm wage effect is a stronger predictor of job mobility among men than among women, while the opposite is true for commuting time. Taken at face value, women require a wage increase to compensate for a longer commute that is twice as large as the corresponding increase required by men.

Our findings contribute to several strands of the literature. First, we add to the literature about gender differences in pay by highlighting the relevance of a specific mechanism behind the within-firm gender wage gap – the fact that female wages are less responsive to outside job opportunities compared to male wages. There is very little direct evidence on the role of such gendered responses. One exception is Blackaby et al. (2005): in a study of UK economists, they found that outside offers (observed directly in survey data) are associated with higher earnings for men but not for women. In relation to this study, we provide evidence that plausibly has a causal interpretation in a broader setting.

Second, our paper sheds light on the mechanisms behind the gendered responses to outside offers. Most of the early studies on negotiation differences are conducted in controlled experimental settings or based on subgroups of the population.[6] It is therefore not clear that this mechanism is economically relevant in explaining the overall gender pay gap (Bertrand 2011). Recently, a few studies have provided new insights from real labor market settings. Biasi and Sarsons (2022) analyze the link between flexible pay and the gender wage gap among teachers, and find that flexible pay lowered the salaries of women relative to their male counterparts. Survey responses indicate that female teachers are substantially less likely than men to have negotiated their pay at various points in their careers. Caldwell et al. (2024) document gender negotiation differences in the German labor market. Similarly, Olsson and Skans (2024) show that the (within-job) gender pay gap among Swedish blue-collar workers is related to the degree of wage flexibility within the firm, while Illing et al. (2023) show that the gender entry pay gap in Germany is lower in jobs within less occupational wage variance. Another related paper is Roussille (2024) who finds that female workers declare significantly lower starting wages on an online hiring platform for high-skilled workers, which translates into lower wage bids and offers.[7] Our paper contributes to this growing body of research by isolating the impact of improvements in outside opportunities for the gender pay gap, and the differential job mobility responses among women and men.

Third, the paper adds to a recent line of reduced-form evidence on the role of outside options for wages more generally (Jäger and Heining 2022, Jäger et al. 2024). Ek et al. (2024) construct an empirical measure of job match quality (based on information about worker skills) and show that the wage returns to match quality respond to local labor market conditions; as their measure is based on data from the military conscription, their analysis is confined to male workers. Caldwell and Harmon (2019) show that increases in labor demand at former coworkers' current firms lead to job mobility and wage growth in Denmark. Because they focus on professional networks, where network quality may vary systematically across men and women, their strategy is not well-suited to study gendered responses to outside options. Di Addario et al. (2023) focus on the relevance of outside options for the individual variation—as well as, the gender gap—in starting wages. In relation to their study, our focus is on the role of outside options for the within-match wage growth of men and women.

Fourth, we add to the literature highlighting that women prefer—and are willing to pay for—shorter commutes, partly to be able to combine work with family commitments (Le Barbanchon et al. 2021, Fluchtmann et al. 2024).[8] Such preferences may not only explain the gender wage gap through a sorting channel (the main focus in previous work) but also drive wage inequalities in existing jobs through on-the-job offers and counteroffers. In recent work, Caldwell and Danieli

[6]For reviews see Bowles et al. (2005); Bowles and McGinn (2008); Stuhlmacher and Walters (1999); Bertrand (2011); Mazei et al. (2015); Kugler et al. (2018); and Hernandez-Arenaz and Iriberri (2018).

[7]Säve-Söderbergh (2019) uses survey data on recent social science graduates in Sweden and shows that women submit lower wage bids than men and are also offered lower wages. Additionally, women receive lower counter-offers than men.

[8]Both these papers study gender-differences in commuting preferences among the unemployed.

(2024) provide an individual measure of outside options based on the concentration of similar workers across jobs in Germany. They show that women's options are more limited due to commuting constraints, which contributes to the gender pay gap. Our results are well in line with this literature: In particular, while commuting time lowers job mobility for both genders, it is a stronger predictor for women. Moreover, our estimates suggest that the compensating wage differential for distance is higher for women than for men.

Finally, we contribute to the literature about the role of informal networks for gender pay differentials. This literature has mainly focused on women's lack of professional networks as a source of gender inequality, particularly at the top of the wage distribution (Essen and Smith 2023). As a complement, our paper informs about the gender differences in rent-extraction from network job opportunities (of the same average quality).

The remainder of the article is organized as follows. It begins by presenting our theoretical framework in Section 2. Section 3 describes the institutional context and provides evidence on the gender wage gap in the Swedish labor market. In Section 4 we describe our data and construction of key variables and present summary statistics. Section 5 outlines the empirical strategy. Sections 6 and 7 present the main results on the impact of outside opportunities on male and female wages and job mobility and Section 8 discusses alternative explanations and presents validation checks. Section 9 concludes.

2 Framework: Outside options and the gender wage gap

Here we develop a stripped down model of on-the-job search and wage bargaining, which we use as a guide to the interpretation of our results. Our partial equilibrium framework captures the essential features of a Postel-Vinay and Robin (2002) model. Firms thus bargain with workers, both at the beginning of the employment relationship and when the worker receives a credible outside offer. The fundamental questions of interest are the following: To what extent do outside job opportunities impact wages within an ongoing employment spell? How big is the impact of outside offers on job-to-job mobility? And, ultimately, how do outside options shape the within-firm gender wage gap?

The comparative static changes considered here correspond well to our empirical setting. Since we measure outside options using information on whether there is a job opening in the family network, the characteristics of the family network do not vary by gender. The differences across women and men thus do not stem from differential offer arrival rates in our empirical setting.

Our framework considers two types of differences between women and men. First, we assume that women are more sensitive to the length of the work commute. With a shorter maximum acceptable commute, a smaller fraction of job offers will be acceptable for women compared to men (see Le Barbanchon et al. 2021 for empirical evidence). Second, we assume that women are less willing to negotiate their wages compared to men. This assumption lines up with evidence surveyed by Bertrand (2011), where women perceive it as more costly to bargain. In particular, we assume that women primarily bargain at the start of the employment spell, and not within an ongoing spell. These two assumptions have the same implications for wages: women are thus paid less than men within firm, and women's wages within an employment spell are less impacted by an improvement in outside options (see, e.g., Card et al. 2016 on evidence of gender differences in rent sharing). However, they have opposite implications regarding the impact on job-to-job mobility.

Of course, we could have maintained other assumptions. For instance, women may be less apt to extract match-specific rent compared to men. However, such differences in "bargaining skill" will largely be isomorphic to differences in preferences vis-a-vis commuting (Card et al. 2016). We could also have assumed that women have more particular preferences regarding other job attributes than wages compared to men. Again, the implications will be analogous to gender differences in commuting preferences.

2.1 The basic set-up

We are interested in the outcomes for employed workers. There are two types of workers, $M = \{0, 1\}$, where $M = 0$ for women. Consider a worker of type M who is employed at a firm with productivity y. This job pays a wage $w(y, y_{-1})$, where y_{-1} denotes productivity associated the previous next-best offer (this could also be the value of unemployment, b, which we assume is constant across worker type). There is random on-the-job search. A worker of type M samples a relevant job offer at rate $\lambda(M) = \lambda\delta(M)$, where λ is the job offer arrival rate and $\delta(M)$ is the probability that members of group M find the commute acceptable. Given an acceptable offer, the worker draws new productivity y'. Conditional on location, we take productivity to be the only dimension along which jobs differ. If $y' > y$, the worker moves to a new job. If $w(y, y_{-1}) < y' < y$, the worker opens up renegotiation; the new wage is then given by $w(y, y')$. Finally, there is the possibility that the offer is such that $y' \leq w(y, y_{-1})$ in which case the worker retains $w(y, y_{-1})$.

In this framework, wages are affected by bargaining strength (β) as well as counteroffers. Following Cai (2020), we take the wage to be given by

$$w(y, y_{-1}) = \beta y + (1 - \beta) y_{-1} \tag{1}$$

for a worker who is in a job with productivity y whose next-best offer is y_{-1}. This is the outcome of a strategic alternating bargaining game (of the Rubinstein 1982 type) if the risk of an exogenous break-up of the bargain is ignorable. There is thus within-firm wage dispersion across groups since workers have received acceptable outside offers at different rates.

The basic intuition of the model can be illustrated by defining a given workers' share of the total surplus (η). It equals

$$\frac{w - b}{y - b} = \beta + (1 - \beta)\frac{y_{-1} - b}{y - b} = \eta(y, y_{-1}, b) \tag{2}$$

A worker whose next best offer is b, receives β of the total surplus. When $y_{-1} \to y$, the worker receives the full surplus of the current match: $\eta \to 1$.

This is the basic structure. Going forward, we invoke two convenience assumptions. First, we follow a given set of employed workers over three periods (0, 1, and 2). In period 0, workers and firms match, and agree on a wage $w(y, b)$; in period $t > 0$ they obtain alternative offers at rate λ_t and draw alternative productivity from the distribution $F_t(y')$. We take period 2 to be the period of observation in our empirical work. Three periods is the minimum number of periods that allows workers to have different rates of wage progression prior to the current job. Second, we assume that the underlying productivity distribution is uniform on the $(0, 1)$ interval. This simplifies the expressions without changing the substance.

In our empirical work, we examine whether outside offers – as measured by hiring at a firm to which the worker is connected – influence on-the-job wage growth and the probability of a job-move. Family connections thus generate exogenous variation in the offer arrival rate λ. In terms of the model, average wages among workers who stayed at a job with productivity y is given by:

$$E(w_t|\, M, \lambda, y, y' < y) = w(y, b) + (1 - \beta)\left\{E\left[y'\middle|\, y, y' < y, j = 1\right] - b\right\}\psi(M, \lambda, y, y' < y) \quad (3)$$

where $j = 0, 1, 2$ denotes the number of wage updates and

$$\psi(M, \lambda, y, y' < y) = \left\{\Pr\left[j \geq 1|\, M, \lambda, y, y' < y\right] + \frac{1}{2}\Pr\left[j = 2|\, M, \lambda, y, y' < y\right]\right\}$$

ψ measures how frequently the wage has been updated and is thus a measure of wage progression. For obvious reason it is increasing in the arrival rate of acceptable offers.

The probability of moving to another job is

$$\mu_t(M, y) = \lambda_t \delta(M) \Pr(y' > y) = \lambda_t \delta(M)(1 - F_t(y)) \quad (4)$$

2.2 Commuting aversion among women

Suppose now that women are averse to commutes; therefore, a smaller fraction of offers are acceptable to them.[9] In particular, assume that $\delta(M) = (1 - d(1 - M))$. Thus, the rate of acceptable offers is λ for men, while it is $\lambda(1 - d)$ for women.

This assumption has several implications.[10] First, women are paid less than men within-firm, on average; the within firm gender wage gap, $\Delta = E(w_t|\, M = 0, \cdot) - E(w_t|\, M = 1, \cdot)$, is thus negative:

$$\Delta = (1 - \beta)\left\{E\left[y'\middle|\, y, y' < y, j = 1\right] - b\right\}\left[\psi(M = 0, \cdot) - \psi(M = 1, \cdot)\right] \quad (5)$$

where $[\psi(M = 0, y, \cdot) - \psi(M = 1, y, \cdot)] < 0$. Women do not have the same possibility as men to increase their wages using outside options, when a smaller fraction of offers are relevant for them.

Second, and for analogous reasons, women's wages are less responsive to the arrival rate of

[9] A common assumption in the literature is that women's non-market time is more productive than men's, e.g. because they are responsible for the bulk of household and child-rearing tasks. In this case, the opportunity cost of commuting time would be higher for women than for men (and for mothers than for non-mothers).

[10] Appendix A contains an extended description of the model, and derives the implications formally.

outside offers than the wages of men.

$$\frac{\partial \Delta}{\partial \lambda_t} = (1-\beta)\left\{E\left[y'\middle|\, y, y' < y, j=1\right] - b\right\}\left[\frac{\partial \psi(M=0,\cdot)}{\partial \lambda_t} - \frac{\partial \psi(M=1,\cdot)}{\partial \lambda_t}\right] < 0 \tag{6}$$

Third, job-to-job mobility among women is less responsive to the arrival rate of job offers than among men.

$$\frac{\partial \mu_t(M=0,\cdot)}{\partial \lambda_t} - \frac{\partial \mu_t(M=1,\cdot)}{\partial \lambda_t} = -d(1-F_t(y)) < 0 \tag{7}$$

Our empirical results suggest that women and men move to similar extents, which implies that many offers are about as relevant for women as they are for men. To capture the full range of the possible differences between women and men, we turn to a model focusing on women's aversion to renegotiation.

2.3 Renegotiation aversion among women

Consider a setting where women find it costly to renegotiate wages (to focus on this particular mechanism, set $d = 0$). Assume that such costs are so high that no woman renegotiates their wages with their current employer; the only time when women negotiate their wages is at the start of a new employment spell.[11] This also implies that women move whenever the productivity associated with an offer is higher than the wage in the current match (denoted $w(y, y_{-1})$ below).

For women, the expected wage among stayers in a job with productivity y is given by

$$E(w|\, M=0, \lambda, y, y' < w(y, y_{-1}) = w(y,b) + (1-\beta)\beta\left\{E\left[y'\middle|\, y, y' < w(y, y_{-1}), j=1\right] - b\right\}\tilde{\psi}(M=0,\cdot)$$

where

$$\tilde{\psi}(\lambda, M=0, y, y' < w(y, y_{-1})) = \Pr\left[j=1\middle|\, y, y' < w(y, y_{-1}), \lambda\right]$$

Men behave as in the baseline model. Thus, equations (3) and (4) apply to them.

Again, the gender wage gap is negative.

$$\Delta = (1-\beta)\left\{\underbrace{\left[\tilde{\psi}(M=0,\cdot) - \psi(M=1,\cdot)\right]}_{\text{(i) fewer wage adjustments}}\left[\bar{y}_s^{M=1} - b\right] + \underbrace{\left[\beta(\bar{y}_s^{M=0} - b) - (\bar{y}_s^{M=1} - b)\right]}_{\text{(ii) lower wage adjustments}}\tilde{\psi}(M=0,\cdot)\right\} < 0 \tag{8}$$

where $\bar{y}_s^{M=0} = E\left[y'|\, y, y' < w(y, y_{-1}), j=1\right]$ and $\bar{y}_s^{M=1} = E\left[y'|\, y, y' < y, j=1\right]$, implying $\bar{y}_s^{M=0} < \bar{y}_s^{M=1}$. For individuals who stayed in a job of given productivity y, wages among women are lower for two reasons: (i) since women do not open renegotiation with their current employer, their wages have been adjusted on fewer occasions compared to men: $\tilde{\psi}(M=0,\cdot) < \psi(M=1,\cdot)$; (ii) when women locate a new employer, they use the wage with their current employer as the outside option in the negotiation; when women move to a new employer, their outside option

[11] Formally, a model where no employer renegotiates wages with women is isomorphic to the current one. We emphasize women's renegotiation aversion because this is consistent with the empirical results in the previous literature; see Caldwell et al. (2024), for example.

is thus lower than for men, since men are able to extract all the surplus from the previous employer.

Women's wages within the current match do not respond to the arrival rate of outside offers (by assumption). And thus

$$\frac{\partial \Delta}{\partial \lambda_t} = -(1-\beta)\left\{\bar{y}_s^{M=1} - b\right\}\frac{\partial \psi(M=1,\cdot)}{\partial \lambda_t} < 0 \tag{9}$$

The impact on job-to-job mobility among women is higher, however. Men move whenever the productivity associated with the offer is higher than the productivity associated with the current match: $\lambda_t(1-F_t(y))$. Women, on the other hand, move if the prospective employer can pay higher wages than the wage in the current match; that is, if $\tilde{\mu}_t(M=0,\cdot) = \lambda_t(1-F_t(\bar{w}(y)))$, where $\bar{w}(y) = E\left[w(y,\cdot))\right]$ denotes the average wage among women in a job with productivity y.[12] Since $\bar{w}(y) < y$, this version of the model predicts that the mobility response to a change in λ_t is higher among women than among men:

$$\frac{\partial \tilde{\mu}_t(M=0,\cdot)}{\partial \lambda_t} - \frac{\partial \mu_t(M=1,\cdot)}{\partial \lambda_t} = F_t(y) - F_t(\bar{w}(y)) > 0 \tag{10}$$

2.4 Summary and discussion

If we combine the two versions of the model – that is, if women are averse to commuting as well as renegotiating wages, the within-firm gender wage gap is negative and grows with tenure. Moreover, women's wages will be less responsive to an improvement in outside options than men's wages. In particular, the impact on women's wages is given by

$$\frac{\partial E(\,w|\,M=0,\cdot)}{\partial \lambda_t} = (1-\beta)\left\{E\left[y'|\,y, y'<y, j=1\right] - b\right\}\frac{\partial \psi(M=0,\cdot)}{\partial \lambda_t(M)}(1-d)(1-\rho) \tag{11}$$

where ρ denotes the share of women who is averse to renegotiation.

However, an improvement in outside options has an ambiguous impact on the gender differential in job-to-job mobility. We have

$$\frac{\partial \tilde{\mu}_t(M=0,\cdot)}{\partial \lambda_t} - \frac{\partial \mu_t(M=1,\cdot)}{\partial \lambda_t} = \underbrace{-d(1-F(y))}_{\text{commuting aversion (-)}} + \underbrace{(1-d)\rho[F(y)-F(\bar{w}(y))]}_{\text{renegotiation aversion (+)}} \tag{12}$$

In the sequel, we present evidence suggesting the women's wages are unaffected by outside offers, but that they respond to outside opportunities by moving to the hiring establishment at almost the same rate as men. This suggests that the outside offers we consider are relevant, that is $d << 1$. However, because most women are averse to renegotiation, outside offers are not used to bargain wages in existing matches, i.e., $\rho = 1$.

[12] Here (and at other places) we use that the distribution of productivity is uniform.

3 Institutions and context

The Swedish labor market is governed by collective agreements, formed at the industry level with separate agreements for white- and blue-collar workers within these industries. The vast majority of workers are covered and the agreements stipulate the terms of employment, including the wage setting process. The process has three stages. First, unions and employer organizations form central agreements, setting the frame for wage formation. Then, bargaining at the local (establishment) level occurs, where the local union and firm representatives translate the central agreement to the establishment level. Finally, wages at the individual level are negotiated between the manager and the worker.

The scope for individual bargaining varies across agreements, but is generally larger for white-collar than for blue-collar workers.[13] In practice, this means that wages are set in bilateral negotiations between the employer and its white-collar employees; typically, the agreements stipulate a fall-back wage increase that becomes relevant only if the local bargaining fails (Fredriksson and Topel 2010).

Sweden is known for its high gender equality compared to other (non-Nordic) countries. The employment and labor force participation rates for women in Sweden are among the highest in the world, and there are relativity small employment differences between men and women, although part-time work is more prevalent among women.[14] Despite comparatively high gender equality in terms of employment important systematic differences remain. In Table 1 we report the gender wage gap in Sweden estimated in representative register data (explained in detail below). The adjusted hourly gender wage gap in the period we study is 11 percent overall and 16 percent for white-collar workers – more than twice the gap for blue-collar workers. Approximately 40% of the gap is due to sorting of men and women across occupations, suggesting that occupational gender segregation is pervasive. But even when comparing male and female workers in the same job (within occupation×establishment) we find a wage gap of 8.4 percent (2.7 percent among blue-collar workers). Hence, wage outcomes of men and women differ substantially even after controlling for demographic and labor market characteristics.

An implication of the framework outlined in Section 2 is that the gender pay gap should grow over the employment spell as male workers extract a larger share of the rents trough counteroffers. Consistent with this, Figure 1 shows how the wage gap between men and women in the same job diverge with tenure: the gap grows with about 0.4 percentage points annually over the first seven years in the firm. Of course, there may be other explanations for these dynamics. Gender differences in turnover rates or accumulation of firm-specific human capital may have the same implications for the association between the gender wage gap and tenure as gendered responses to outside job offers. In our main empirical analysis we therefore leverage job opportunities emerging within the social network to examine the role of outside opportunities for gender differences in pay.

[13] This difference between blue- and white-collar workers reflects the traditional view that blue-collar workers have higher substitutability, which motivates that the characteristics of the job primarily determine the salary. The trade unions on the white-collar side have instead signed wage agreements where the individual's characteristics are primarily decisive for the salary.

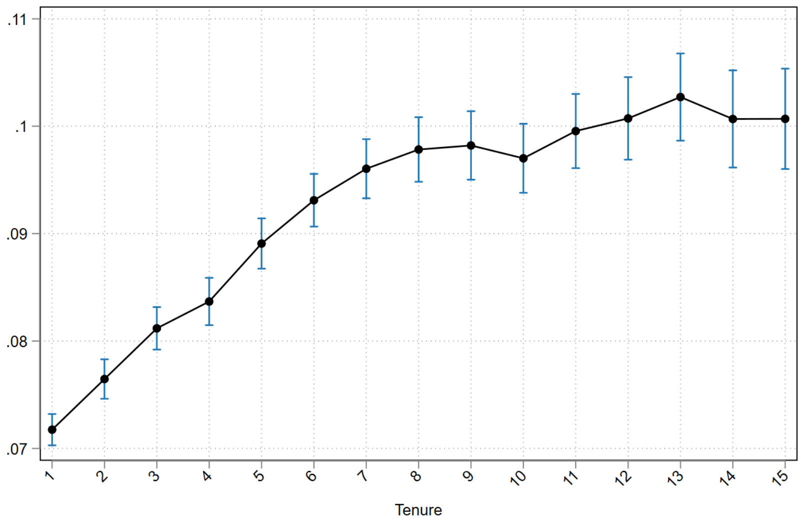
[14] In 2017, the labor force participation rates for women and men aged 20–64 were 85% and 89%, respectively. The corresponding employment rates were 80% and 84%, respectively.

Table 1: Gender Wage Gap in Sweden

	(1) All	(2) White Collar	(3) Blue Collar
Raw	-0.11	-0.17	-0.082
	(0.000)	(0.000)	(0.000)
Within occupation	-0.082	-0.10	-0.039
	(0.000)	(0.000)	(0.000)
Within establishment	-0.10	-0.14	-0.035
	(0.000)	(0.000)	(0.000)
Within job (establishment $\times$ occupation)	-0.067	-0.086	-0.026
	(0.000)	(0.000)	(0.000)
Observations	10,777,541	6,501,253	4,276,288

Note: The table shows the estimated coefficient on an indicator for being a woman in individual-level wage regressions with log hourly wage as the dependent variable. All regressions include age, education and year dummies. Occupations are measured at the three digit level. The estimation sample includes all private sector workers in the Swedish Wage Structure Statistics (WSS), explained in more detail in Section 4.

Figure 1: Evolution of the gender pay gap with tenure



Note: The figure shows the estimated coefficient on an interaction term between an indicator for having male gender and years of tenure within the plant. The sample is restricted to white-collar workers and corresponds to the sample in Column (2) of Table 1. The regression specification include flexible controls for age interacted with educational attainment as well as *establishment* $\times$ *occupation* $\times$ *year* fixed effects.

4 Data

4.1 Data sources and sample selection

The data we use cover the Swedish population during 2006–2018. They include linked information on individuals, establishments and firms, and individual demographic information along with family links. Below, we describe the main components of our data in more detail.

Workers, employers and worker mobility: Our primary data source is linked employer-employee data covering the entire Swedish working age population.[15] In these register data we identify each employment spell, including the first and last month of employment. We define a worker's main job as the employment relationship that yields the highest annual income among all job spells in a year.[16] In addition, we exclude self-employed workers to prevent job-to-job transitions to and from family businesses. We drop individuals whose monthly earnings are lower than 80 percent of the minimum wage.[17] We use the employment registers to define hires, separations, and tenure. We define a *new hire* as a worker who started working at an establishment for the first time.[18] We define *separations* when a worker is observed at the establishment for the last time to avoid defining recalls and parental leave as separations. *Mobility to connected employer* is defined as a move to an establishment in year $t+1$ where any of the connections worked in year t. Tenure is the number of years (not necessarily consecutive due to temporary leave) the person has worked in a given establishment since 1985.

Demographic data are drawn from Statistics Sweden's LOUISE register, including the entire Swedish population aged 16 to 74. These data include demographic information such as year of birth, gender, and the highest completed education (both the level and field of study).

We use a supplementary firm and establishment register (FtgAst) to obtain information on the establishment's location and industry.[19] Location is defined by a so called "DeSO"-code, a statistical area defined by Statistics Sweden to resemble a neighborhood.[20]

Wages: Information about wages come from a firm level survey conducted by Statistics Sweden (Wage Structure Statistics (WSS)). Sampled firms must report individual-level wages for all workers aged 18 and 66. Wage data are collected during a measurement week in September through November, and include workers who have worked at least one hour with pay. WSS data cover the entire working population in the public sector and about 50 percent of the workers in the private sector. The sampling of private sector firms is based on firm size.[21] Since the sampling probability depends on firm size, small establishments belonging to larger private firms have a high chance of being included. The wage reflects the employee's wage during the sampling month expressed in full-time monthly equivalents. All wage components, e.g., piece-rate and performance pay, except overtime pay, are included.[22]

[15] These data are collected from tax registers, and the reporting is mandatory.

[16] In other words, we include multiple job holders, but focus on their main source of income.

[17] We take the minimum wage to equal the 5th percentile in the wage distribution among blue collar workers.

[18] An establishment is defined by Statistics Sweden from the combination of firm and location.

[19] The most detailed industry codes are at the five-digit level. We aggregate this information to the two-digit level, and group the 88 different industry codes into 21 broad categories.

[20] The DeSO-code divides Sweden into 5,984 areas. https://www.scb.se/hitta-statistik/regional-statistik-och-kartor/regionala-indelningar/deso—demografiska-statistikomraden

[21] Firms with more than 500 employees are always included.

[22] The survey also collects information about occupations at the 4-digit level (SSYK, corresponding to ISCO-

Family links: We use multi-generational population-wide birth records (Flergenerationsregistret) to establish family connections. These data allow us to link each individual to their parents, enabling the construction of full and half-siblings in addition to parental links.

4.2 Construction of outside options

In our analysis, we measure outside options as the sum of the employment changes at the establishments to which workers are connected via family members.

As firms report their employees' wages in the measurement week in September through November, we predate our outside options measures focusing on hires in connected establishments occurring between January$_t$ until the end of September$_t$ in a given year. Recognizing that not every job opening or hire can be considered a relevant outside option for the worker in question, we focus our main attention on job openings within the same occupation, proxied by the education field.[23] Our measure of the individual- and time-specific outside options (Ω_{iot}) is, thus, the employment change in the same 3-digit education field as the worker in question at connected establishments:

$$\Omega_{iot} = \sum_{j' \neq j} \left(\text{Hires}_{j',o,t_{1,9}} \right)$$

where i denotes worker, j' the connected establishment(s), o the occupation of the new hires, and $t_{1,9}$ the first nine months of the year. Outside opportunities vary for individuals within job spell over time as well as across individuals in the same job (plant-by-occupation).[24] Our empirical approach relies on the idea that workers with family members employed at different establishments have private information about available positions in those workplaces compared to other workers. In most of our empirical work, we will focus on a binary indicator for having at least one outside option, which we denote OO_{iot}.

4.3 Sample and summary statistics

We construct an individual panel data set at the annual frequency and deflate wages to 2015 Swedish Kronor (SEK). In the main analysis we restrict attention to white-collar workers in the private sector as wages are more flexible for this group of workers with larger scope for individual wage bargaining. Additionally, this is the segment of the labor market where gender wage differentials are most pronounced (see Table 1).

Our final sample consists of private sector white-collar employees with at least one employed connection, excluding self-employed from each side.[25] Furthermore, we keep connections in

88). However, due to the sampling issue we will mainly rely on education field to proxy for occupations, as this information is available for the full population of interest.

[23] We rely on the 3-digit level of the Swedish education code (SUN) to measure relevant job openings in all connected firms. We use it to proxy occupations; the advantage of the education information is that available for everyone, whereas occupations are only available for the sample of firms included in the WSS.

[24] Our focus on employment changes in connected firms is similar to Caldwell and Harmon (2019). We differ by focusing on gross instead of net hires, narrowing our focus to variation within the same occupation as the focal worker, and, importantly, by focusing on family networks rather than professional networks. In Section 6 we show that our results are not sensitive to the choice of gross versus net hires. Relaxing the occupation requirement attenuates the results somewhat but does not change the main conclusions.

[25] We exclude those who do not have any family link, or have a link who is not employed in that year.

establishments with at least two employees (including the connection).

Table 2 provides summary statistics, overall and separately by gender. A majority of the workers in our sample - 57 percent - have a college education reflecting that we focus on white collar workers in the private sector.[26] Age and education levels are very similar across the genders. There are large gender disparities in the occupation of employment, however: women are over-represented in clerical and service occupations while men are more likely to work in managerial occupations and in high skilled professions (Panel C). Women have 16 percent lower hourly wages. Appendix Table C1, shows that the within job gender pay gap conditional on observables is almost identical in the estimation sample as in the pay gap illustrated in Table 1 for the economy wide data.

Panel B also shows that women have 4 percentage points higher separation rate than men. Distinguishing between different types of job separations shows that this pattern is driven by a higher female propensity to separate to non-employment. In contrast, job-to-job mobility rates are the same for males and females suggesting that employers cannot exploit women's lower willingness to move in general.[27]

Panels D and E of Table 2 show summary statistics on family links and outside opportunities. Women and men have the same number of employed family links, on average. Workers are exposed to on average 7 job openings in their connected establishments within a year, and 45 percent of workers have at least one job opening during the observation window. Around 3/4 of the job openings occur in establishments to which workers have a sibling tie, and one-fourth occur in establishments where a parent is employed. On average, the probability of having at least one outside opportunity is balanced across the genders.

Finally, Panel F shows that women work at smaller establishments located closer to the home compared to men. While the average distance to the connected plants is longer, it is more similar across the genders compared to the commuting distance to their actual employer.[28]

5 Empirical strategy

5.1 Measuring the wage returns to outside opportunities

To examine the gender-specific wage and mobility responses to changes in the outside opportunities, we estimate the following equation, separately for male and female workers:

$$Y_{ijt} = \beta_1 \mathrm{OO}_{iot} + \alpha_{ij} + \alpha_{jt} + \alpha_{ot} + X_{it}'\delta + \epsilon_{ijt} \tag{13}$$

where Y_{ijt} represents the outcome of interest (wage or job mobility) of worker i in establishment j measured in September each year t. OO_{iot} takes the value one if the worker had at least one job opening in a connected establishment between January and September in year t. OO_{iot}

[26] The share of college educated among blue-collar workers is around 8.7 percent (see Table C3).

[27] Appendix Table C2 confirms this finding by showing the estimated within-job gender gap in job-to-job mobility, conditional on age and education. These estimates suggest that the mobility difference between men and women is negligible.

[28] Distance is calculated (in kilometers) between the centroid of the residence DESO, the current establishments' DeSO and the the linked establishment's DESO. Figure C1 shows the distribution of commuting distance for men and women and for the current and connected plant.

Table 2: Sample statistics

	All workers	Male workers	Female workers
	(1)	(2)	(3)
Panel A. Age and Education			
Age	42.9	42.9	42.8
Compulsory or less	0.045	0.049	0.040
High school	0.39	0.38	0.40
College	0.57	0.57	0.56
Panel B. Wages and separations			
Log hourly wage	5.40	5.47	5.31
Within-job wage growth	0.028	0.028	0.028
SD(Within-job wage)	0.085	0.089	0.080
Var(Within-job wage growth)	0.012	0.013	0.011
Separation	0.16	0.14	0.18
Separation to any plant	0.11	0.11	0.11
Separation to non-employment	0.044	0.028	0.067
Panel C. Occupations			
Legislators, senior officials, and managers	0.14	0.16	0.10
Professionals	0.33	0.34	0.31
Technicians and associate professionals	0.36	0.38	0.32
Clerks	0.11	0.061	0.19
Service workers and shop sales workers	0.037	0.021	0.061
Panel D. Family links			
Number of family links	4.06	4.06	4.08
Number of employed family links	1.78	1.77	1.78
Number of employed parents	0.41	0.41	0.40
Number of employed siblings	1.37	1.36	1.37
Share of males in network	0.52	0.52	0.51
Panel E. Outside opportunities			
Number of outside opportunities (Ω_{it})	140.9	140.8	141.0
Number of outside opportunities in own occupation (Ω_{iot})	7.08	6.51	7.92
At least one outside opportunity in own occupation (OO_{iot})	0.45	0.46	0.44
OO in parents' plant	0.11	0.11	0.11
OO in siblings' plant	0.38	0.39	0.37
Panel F. Establishments			
Plant size	41.5	45.1	37.7
Distance: home to current plant (km)	24.0	26.7	20.0
	(8.83)	(9.60)	(7.89)
Distance: home to connected plant (km)	121.8	122.5	120.7
	(35.9)	(37.2)	(34.0)
Observations	4616511	2749099	1867412

Note: The table shows the mean characteristics of all white collar workers, male and female workers in columns 1,2, and 3, respectively. Medians are reported in parenthesis for distance to current plant and distance to connected plant.

thus captures variation in labor demand specific to individuals and time, through job openings available within the family network.

Our analysis incorporates three distinct sets of fixed effects. First, since we are primarily interested in within-job wage growth, we include worker-by-establishment, or spell, fixed effects (α_{ij}). The identifying variation in specification (13) comes from individual-specific changes in the exposure to (information about) potential job opportunities, accounting for all permanent aspects of worker heterogeneity.[29] Second, we include establishment-by-year fixed effects (α_{jt}) to hold labor demand at the establishment level constant. Third, we control for occupation-by-time fixed effects, α_{ot}, to account for changes in occupation-specific labor demand over time.[30] Additionally, the vector X'_{it} includes the average size of the connected plants, the number of employed family links, and age fixed effects. The inclusion of spell fixed effects and age fixed effects is important. The other controls do not matter for our results. To account for correlation in wage growth among employees within the same workplace, occupation, and year, as well as correlated mobility preferences, we cluster our standard errors at the establishment-occupation-year level.

The coefficient β_1 reflects the response to individual-specific changes in outside opportunities. According to the theoretical framework outlined in Section 2, we hypothesize that $\beta_1^{male} > \beta_1^{female}$, i.e. women's wages will be less responsive to improvements in outside options compared to men's, while the differential mobility response has an ambiguous sign.

Identification of β_1 relies on the random timing of exposure to outside opportunities. We explore the validity of this assumption using a dynamic model of specification (13). Furthermore, it is crucial that the quality of outside job offers is uncorrelated with gender.[31] In the next section, we provide evidence supporting this assumption.

5.2 Gender balance in the quality of outside opportunities

If women are exposed to outside offers of lower (or higher) average quality, this could bias the coefficients of interest. This possibility is examined in Figure 2, which relates gender to characteristics of the connected expanding establishments using the following model:

$$Q_{ij't} = \gamma Female_i + \alpha_{jt} + \alpha_{ot} + X'_{it}\delta + \epsilon_{iojt} \tag{14}$$

where $Q_{ij't}$ captures characteristics of connected establishment j', and $Female_i$ indicates whether worker i is female. As above we include establishment-by-year fixed effects (α_{jt}) and occupation-by-year fixed effects (α_{ot}) and X'_{it} are defined as in Equation 13. Figure 2 presents the estimates of γ for various measures of connected establishment quality. The results suggest that the expanding employers to which men and women are connected are very similar in terms of AKM wage premia, productivity and other alternative measures of employer attractiveness.[32] For instance, family network expansions are balanced across genders in terms of the fraction of new hires that are "poached" from other employers, their exit rates and geographical distance. Overall, there is no evidence of significant differences in the quality of network job opportunities

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[29] As such, the specification also handles the concern that the propensity to have employed family members is correlated with unobserved productivity.

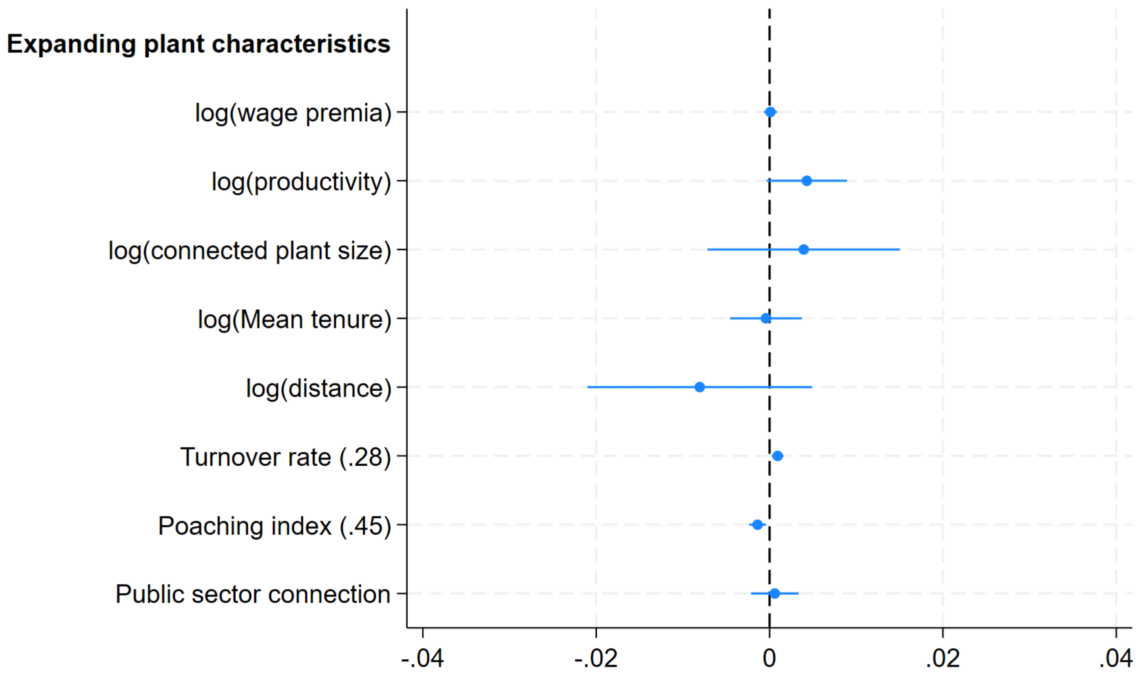
[30] While the construction of the outside opportunities relies on education codes to proxy for occupations, the occupation-by-time fixed effects use 3-digit occupation codes from the Swedish nomenclature for occupations (SSYK, corresponding to ISCO-08). The reason for using education codes for the expansions is that the actual occupation codes are only available for a subsample of workers while education codes are available for everyone.

[31] In the model, we assume that men and women draw alternative productivity from the same distribution ($F_t(y')$).

[32] The establishment-level wage premia is estimated using the AKM model of Abowd et al. 1999 with worker and establishment fixed effects given by equation 16 in section 7.3.

between genders.[33]

Figure 2: Gender gaps in the quality of job openings



Note: The figure shows estimates on an indicator for being a woman, in separate regressions where row headings correspond to the dependent variable. The regression specification includes flexible controls for age, education, establishment x year, and occupation x year fixed effects. The sample is restricted to white-collar workers and corresponds to the sample in Column (1) of Table 2. Where relevant, mean of dependent variables are reported within parentheses.

5.3 Predicted the relevance of new jobs

As discussed in Section 2, not all offers are relevant to the worker. Whether the offer is relevant or not depends on whether the outside firm can pay the worker in excess of the current wage (i.e., it depends on whether $w(y, y_{-1}) < y' < y$.). To get a sense for the fraction of viable offers we divide the network job opportunities into three categories based on the distance between the current wage, $w(y)$ and the highest wage in the current and the new job, y and y':[34]

$$\text{OO}_{iot} = \begin{cases} 1 & \text{if} \quad y' \leq w(y) \\ 2 & \text{if} \quad w(y) < y' < y \\ 3 & \text{if} \quad y' > y \end{cases}$$

Then, we predict the relevance of job offers for renegotiation using the following empirical specification:

[33] For comparison, Appendix Figure C2 shows the corresponding estimates when we consider coworker -instead of family- networks. Consistent with our prior, these are not balanced in their characteristics across gender. In contrast, women are exposed to network job opportunities at less productive firms located closer to the home.

[34] To avoid having to condition on wage data being available for both the current and the new firm we use data on monthly earnings available for everyone for this analysis.

$$\mathbf{1}(\text{OO}_{iot} = k) = \beta_1 \text{OO}_{iot} + \alpha_{ij} + \alpha_{jt} + \alpha_{ot} + X'_{it}\delta + \epsilon_{ijt} \tag{15}$$

where $\mathbf{1}(\text{OO}_{iot} = k)$ indicates whether the job opening belongs to category $k = 1, 2, 3$, and α_{ij}, α_{jt}, α_{ot} and X'_{it} are defined as in Equation (13). The results, shown in Table 3 suggest that for male workers, about 30% of job openings should be relevant for renegotiation. Because women have lower average wages, their renegotiation margin is somewhat larger (32 percent of offers should be relevant). Furthermore, 34 and 40 percent of the network job opportunities is predicted to generate a job move for men and women respectively. We will return to these estimates below when discussing the magnitudes of our main results.

Table 3: Relevance of outside options

	Males	**Females**
Dep. var: OO $= 1$ **(worker should stay in current job)**	0.37	0.28
	(0.00)	(0.00)
Dep. var: OO $= 2$ **(worker should renegotiate)**	0.29	0.32
	(0.00)	(0.00)
Dep. var: OO $= 3$ **(worker should leave)**	0.34	0.40
	(0.00)	(0.00)
Observations	4,722,746	3,177,218
Adjusted R^2	0.38	0.41
Worker x Plant FE	Yes	Yes
Plant x Year FE	Yes	Yes
Occ x Year FE	Yes	Yes
Age FE	Yes	Yes

Note: The table shows regression estimates where an indicator for having at least one OO in one of the three categories defined in connection to equation (15) is the dependent variable. The regressions are at the worker-year-connection level. Each estimate comes from a separate regression. All regressions include the average size of the connected plants and the number of employed family links.

6 Gender gap in wage responses to outside opportunities

Table 4 provides our main results. Columns (1) and (2) report estimates from separate regressions by gender. The estimates reveal very different wage responses for men and women: in years when at least one establishment of a family member is hiring, men's wages increase within an employment spell. Women's wages, on the other hand, remain unaffected. As shown by the p-value at the bottom of the panel, the gender difference in wage returns is statistically significant.

The estimates imply that having a network job opportunity leads to a 0.056 percent increase in male wages. This interpretation is based on the assumption that all job openings are relevant for renegotiation. From Table 3 we conclude that about 30% of the job openings we measure in the data are relevant for renegotiation. Adjusting the estimate for the relevance of the offer, we find that network job opportunities increase the gender pay gap by 0.2 percent, which corresponds to around half of the observed yearly within-spell growth of the gender pay gap (illustrated in Figure 1).[35]

A potential concern with the empirical model is that we compare men and women across employers that may have different bargaining strategies. We explore this in Panel B where we restrict the analysis to a sub-sample of workers in establishment×occupation×time combinations with a mixed gender composition. The results are very similar – if anything they are stronger – compared to our baseline estimates.[36]

Table 4: Wage responses to improvements in outside options

Dep. var: Log hourly wage	Males	Females
Panel A: Full Sample		
OO_{iot}	0.056***	-0.015
	(0.018)	(0.021)
Observations	2,405,671	1,558,234
Adjusted R^2	0.950	0.956
p-value for gender difference		.011
Panel B: Jobs with mixed gender composition		
OO_{iot}	0.070***	-0.022
	(0.021)	(0.025)
Observations	1,786,678	1,106,402
Adjusted R^2	0.951	0.954
p-value for gender difference		.006
Worker x Plant FE	Yes	Yes
Plant x Year FE	Yes	Yes
Occ x Year FE	Yes	Yes
Age FE	Yes	Yes

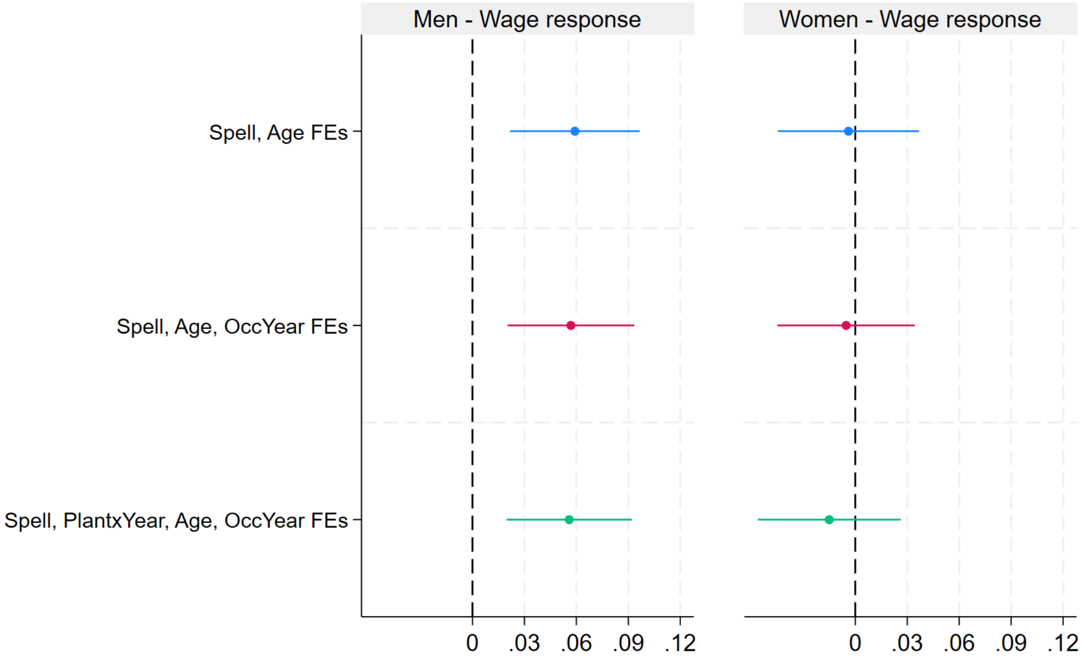
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table shows estimates of log hourly wages in response to OO_{iot} from the main estimating equation 13. We report estimates of β_1 (in columns 1 and 2) separately for men and women. We also report the p-value for the gender difference. Coefficients are multiplied by 100. Panel A shows estimates for the full estimation sample while in Panel B we restrict the sample to workers in jobs with at least one male and one female worker. Standard errors are clustered at the plant x occupation x year level.

Figure 3 shows the sensitivity of our results to alternative specifications of equation (13). The main takeaway is that the results are very stable across specifications. The fact that the results are very similar if we exclude the *plant* × *time* and *occupation* × *time* fixed effects is reassuring as it suggests that the timing of network job opportunities is uncorrelated with demand shocks at the plant and occupation level. Figure 4 shows the dynamic wage patterns around the event of a network job opening. We use a stacked event study design, focusing on stayers between period -1 to period 0, but allowing for worker mobility during the rest of

[35] The estimates in Figure 1 suggest that the within-job gender gap in hourly wages increases by 0.4 percentage points each year during the first 7 years of the employment relationship.)

[36] As an additional check, we reweight the gender-specific regressions so that the distribution of men and women are the same across occupations. In practice, we give each observation in the female regression the weight $w_f o = \#Men_o/\#Women_o$, where o denotes occupation. Again, the results closely align with those in Panel A of Table 4 (see the Appendix Table D1.

Figure 3: Different Model Specifications



Note: The figure shows estimates of β from different specification of the model $ln\, w_{it} = \beta \text{OO}_{iot} + \alpha_{ij} + \alpha_{jt} + \alpha_{ot} + X'_{it}\delta + \epsilon_{ijt}$, where we sequentially add occupation $\times$ year, and plant $\times$ year fixed effects from the first to the last row. We run these regressions separately for men and women. Standard errors are clustered at the plant x occupation x year level. Coefficients are multiplied by 100 and reflect the same magnitudes as in Table 4.

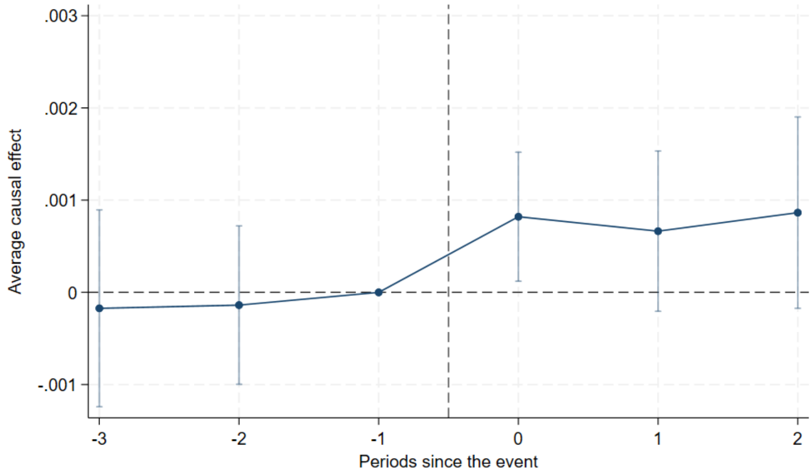
the event window.[37] Reassuringly, the timing of the labor demand shock in a connected plant appears unrelated to the wage trajectory of the worker prior to the event, which strengthens the causal interpretation of the main result.

In Appendix C, we further examine the robustness of the findings in Table 4. Table D1 provides additional robustness checks. Our baseline analysis uses gross expansions. However we obtain similar results using net expansions (Panel B). In addition, we replace the binary indicator of job opportunities with the continuous measure defined in Section 4. We prefer the binary indicator as we do not have to make assumptions about the functional form. Reassuringly however, the take-away from this alternative specification is similar to our main analysis (Panel C).[38] Finally, we relax the restriction that expansions should be in the same occupation as the focal worker's occupation. Removing this restriction attenuates the male wage response slightly, but does not change our conclusions (Panel E).

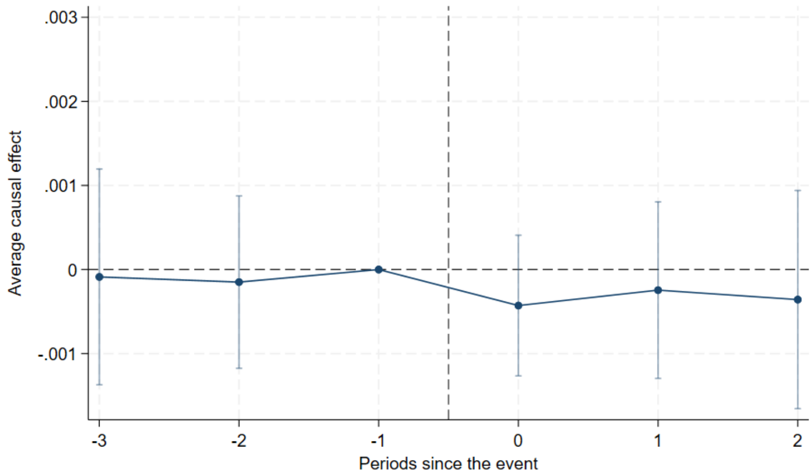
[37]In practice, we restrict the sample to stayers between -1 and 0 and include worker fixed effects and plant$\times$occupation$\times$time fixed effects separately.

[38]Since the estimates now reflect the impact of one additional job opening in the connected plants, the magnitudes are of course smaller.

Figure 4: ASSESSING THE PARALLEL TRENDS ASSUMPTION



(a) MALES



(b) FEMALES

Notes: The figure shows the event study estimates of the β_m parameters in equation $ln\, w_{it} = \sum_{m=-3,m\neq-1}^{2} \beta_m \mathrm{OO}_{io,t-m} + \alpha_{i\times c} + \lambda_{jot} + \lambda_a + \varepsilon_{it}$, along with the 95% confidence intervals. c is treatment cohort, and t calendar year. Standard errors are clustered at the worker level. Sub-panels (a) and (b) display male and female wage responses, respectively, before and after exposure to OO_{iot}. We keep a locally balanced sample of stayers between $t-1$ and t who had at least one employed family member throughout the event window. Note that while the sample is balanced from t–1 to t, appending previous and future years makes it unbalanced due to the connected family restriction and to the sampling in the wage register. Due to the treatment cohort–specific data, we retain workers if the first treatment year is equal to t.

7 Mechanisms: Negotiation aversion vs. job preferences

The results in Table 4 indicate that women's within-match wage growth is unaffected by the arrival of outside options. Based on the discussion in Section 2.4, this finding could reflect either that external job opportunities are not perceived as relevant by women or that these opportunities are relevant but not utilized for wage bargaining within existing matches. In this section, we examine these mechanisms in two ways. First, we examine the job mobility responses of men and women, to assess whether the relevance of offers seems to be systematically different. Second, we replicate our main results for blue-collar workers where individual wage negotiations are generally not possible. If bargaining differences is a key mechanism for why women's wages don't respond to external job opportunities, we expect a smaller gender gap in wage responses when there is less scope for bargaining.

Table 5: Mobility responses to improvements in outside options

Dep. var: Mobility to connected plant	Males	Females
Panel A: Full Sample		
OO_{iot}	0.45***	0.38***
	(0.013)	(0.014)
Observations	2,405,671	1,558,234
Adjusted R^2	0.087	0.095
p-value for gender difference		.00027
Mean dep. variable	.105	.087
Pct impact	430	442
Panel B: Jobs with mixed gender composition		
OO_{iot}	0.47***	0.41***
	(0.015)	(0.016)
Observations	1,786,678	1,106,402
Adjusted R^2	0.085	0.101
p-value for gender difference		.00454
Mean dep. variable	.111	.096
Pct impact	426	427
Worker x Plant FE	Yes	Yes
Plant x Year FE	Yes	Yes
Occ x Year FE	Yes	Yes
Age FE	Yes	Yes

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table shows estimates of mobility to connected plant in response to OO_{iot} from the main estimating Equation (13). We report estimates of β_1 (in columns 1 and 2) separately for men and women. We also report the p-value for the gender difference. Coefficients are multiplied by 100. Panel A shows estimates for the full estimation sample while in Panel B we restrict the sample to workers in jobs with at least one male and one female worker. Standard errors are clustered at the plant x occupation x year level.

7.1 Job mobility

Table 5 examines the job mobility responses of men and women. We use an indicator for separation to a connected employer as the outcome in Equation (13). The estimates aim to capture the impact of external job openings on the probability to accept the offer. A clear positive effect is observed for both genders. Specifically, men's probability of moving into a connected establishment increases by 0.45 percentage points in years when at least one connected establishment expands. While this effect may appear small, it represents a significant increase relative to a low baseline probability, corresponding to more than a fourfold (450%) rise in the likelihood of moving to an establishment employing a family member.

Notably, women's mobility response is very similar to that of men. Although somewhat smaller in absolute terms, the estimate implies a larger proportional impact relative to the baseline. Thus, the outside offers are about as relevant for women as they are for men. However, women do not appear to use these opportunities for wage renegotiation.

7.2 Blue-collar workers

Table 6 presents the wage and mobility responses of blue-collar workers- a group with limited opportunities for individual wage negotiations. Appendix Table C3 provides the summary statistics for this sample.[39] In sharp contrast to the white-collar worker sample, only one tenth of blue-collar workers have a college degree. Their typical occupations include plant machine operators and assemblers (37%), craft and related trades workers (23 %) service and shop sales workers (20 %) and elementary occupations.[40] Despite these occupational differences, their exposure to outside opportunities is very similar to that of the white-collar sample.

Consistent with the notion that wages in this group are set collectively, improvements in individual job opportunities do not lead to wage gains for either male or female employees. However, we observe large job mobility responses for both genders, suggesting that the job opportunities are indeed relevant also for this group of employees. In the Appendix, we also provide heterogeneity results by the occupational wage dispersion for our main, white-collar, sample. In occupations with more compressed wage structures, there is less room for renegotiation. Consistent with this, we only see male wage responses in occupations with above-average wage dispersion (see Appendix Figure C3).[41]

These results reinforce our interpretation that negotiation differences between men and women are a key mechanism underlying the gender gap in wage responses. Consistent with Di Addario et al. (2023), our findings suggest that firms' wage-setting strategies differ across labor market segments.[42] Finally, they underscore that the influence of outside offers on the gender pay gap is closely tied to the extent of individual wage bargaining and the structure of collective agreements, as highlighted in Biasi and Sarsons (2022) and Olsson and Skans (2024).

[39] We apply the same sample restrictions as for the white-collar sample.

[40] Olsson and Skans (2024) demonstrate that wage setting in most blue-collar jobs is governed by rigid contractual arrangements. In line with this notion, blue-collar workers exhibit lower wage growth and less wage variation compared to white-collar workers (See Tables 2 and C3.)

[41] The finding is in line with Illing et al. (2023) who document that the gender pay gap is most pronounced in the occupations in the top of the occupational wage variance distribution.

[42] For the Italian labor market, Di Addario et al. (2023) find that outside options—captured by origin firm effects for job movers— have little impact on starting wages for restaurant workers but are more relevant for workers in law and finance.

Table 6: Blue collar workers

	Wages		Job mobility	
	Males	Females	Males	Females
OO_{iot}	-0.011	-0.050	1.01***	0.83***
	(0.017)	(0.031)	(0.024)	(0.046)
Observations	1,965,512	618,101	1,965,512	618,101
Adjusted R^2	0.829	0.840	0.132	0.117
p-value for gender difference		.27783		.00081
Mean dep. variable			.267	.214
Pct impact			376	388
Worker x Plant FE	Yes	Yes	Yes	Yes
Plant x Year FE	Yes	Yes	Yes	Yes
Occ x Year FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table shows estimates log hourly wages (Panel A.) and mobility to connected plants (Panel B.) in response to OO_{iot} from the main estimating equation 13. The regression sample consists of blue-collar workers. We report estimates of β_1 (in columns 1 and 2) separately for men and women, and β_2 (in column 3) from the full sample. Standard errors are clustered at the plant x occupation x year level.

7.3 Heterogeneity

The individual-level variation in outside options allows us study the heterogeneity of men's and women's wage and mobility responses by external job characteristics, worker characteristics, and worker-job pair characteristics. Based on the theory in Section 2, the mobility response should increase with the productivity of the alternative offer. Since our regressions include spell fixed effects, this is not necessarily the case for the wage response (since the probability of being a stayer is reduced). However, without a mobility response, wages should be monotone in outside productivity. To explore the importance of the productivity of outside offers, we first estimate the AKM model of Abowd et al. (1999) with worker and plant fixed effects:

$$\ln w_{it} = \theta_i + \psi_{j(i,t)} + X_{it}\beta + \epsilon_{it}, \tag{16}$$

where w_{it} is worker i's wage in year t, θ_i is the person-specific effect, and $\psi_{j(i,t)}$ is a plant effect. $X_{it}\beta$ contain year dummies and education-specific age controls as in Card et al. (2013).[43] Figure 5 inter alia considers wage premia of alternative plants. We find that the wage response among men is slightly larger when the worker is connected to an expanding plant that is more productive than the worker's own plant.[44] Women's wages are unresponsive to openings in connected plants no matter the productivity of these openings. Consistent with theory, we find that the mobility response among men and women, is substantially higher for more productive plants.

Second, we explore the role of public vs. private sector job opportunities. Remember that our sample consists of white-collar workers in the private sector. Therefore, jobs at private firms may be considered more relevant compared with jobs at public employers. In line with

[43] We also tried going down to the job-level, which did not change the results.

[44] Appendix Table C4 provides the estimates.

this, we find that the male wage impact documented in Table 4 appears to be driven by job opportunities at other private sector firms (Figure 5). For women, neither private nor public job opportunities translate into a wage increase but job mobility of both genders is higher in response to job openings in the private sector.

Finally, we take a closer look at the role of workplace location. On average, women work at establishments 7 kilometers closer to the home than men. Job openings at connected plants are on average located substantially farther away (see Table 2). We explore this dimension of heterogeneity by differentiating between outside opportunities at firms located closer vs. farther away from the workers' residence relative to the current employer. The results in Figure 5 suggest that male wages respond to job opportunities in a wide geographical area. Mobility responses are stronger when outside opportunities are located nearby both for men and women.

In relative terms, women's mobility appears *less* sensitive to firm wage premia and *more* responsive to commuting time compared to men's.[45] To assess the relative importance of wages vs. commuting distance across the genders, we use the mobility estimates in a back-of-the-envelope calculation of how much wage increase is needed to compensate for the disutility associated with a longer commute for men and women.[46] We conclude that the compensating differential for distance is almost twice as large for women compared with men. The difference between women and men is statistically significant at the 5 percent level. This thus confirms that women's job mobility is constrained by commuting time, as in, e.g., Le Barbanchon et al. (2021) and Caldwell and Danieli (2024).

[45] Differentiating outside job opportunities by local labor market yields very similar results.

[46] Table C5 provides the estimates and Appendix B provides the details of the compensating wage differential calculation.

Figure 5: Heterogeneity by characteristics of the offer

(a) Wage Responses

(b) Mobility Responses

Note: The figure shows estimates of β^A and β^B from the model $Y_{ijt} = \beta^A \mathrm{OO}^A_{iot} + \beta^B \mathrm{OO}^B_{iot} + \alpha_{ij} + \alpha_{jt} + \alpha_{ot} + X'_{it}\delta + \epsilon_{ijt}$, where we distinguish outside opportunities (OO^A_{iot} and OO^B_{iot}) based on whether they originate from higher-/lower-productivity plants, private/public sector, shorter/longer-commute plants, and same/different local labor markets. We run this model separately for men and women. Standard errors are clustered at the plant x occupation x year level. Coefficients are multiplied by 100 and reflect the same magnitudes as in Table 4.

8 Discussion of results

The findings in the earlier sections suggest that, compared to men, women are less likely to engage in wage renegotiations with employers when presented with outside job opportunities of comparable quality.

An alternative interpretation of our findings is that men and women differ in how they use – or value – (family) ties. Our mobility results suggest otherwise. Both men's and women's job mobility respond positively to network-based job openings, indicating that they recognize and take advantage of these opportunities.[47] The same argument holds for other non-wage amenities. If women bargain over other non-wage components they should move to a lower extent than males. The fact that they are substantially more likely to move into high wage plants suggests that pay – rather than non-pay components – is a key driver of women's job mobility decisions. To shed some light on other margins of adjustment, we document labor earnings and hours responses of men and women in Tables E2 and E3. Looking at annual earnings instead of hourly wages provides a similar picture as in our main analysis. Furthermore, there is no indication that women bargain over hours instead of wages as we do not find an hours response – neither for men nor for women.

Because the theory speaks to the impact of external offers on the gender pay gap within the same establishment and occupation, our main results focus on stayers. To shed some light on the effect of external offers on overall wage progression by gender, we estimate the responses with individual rather than spell fixed effects. Thus, we let the main coefficient of interest capture the wage impact of outside job opportunities within and across jobs. The point estimates presented in Table E4 suggest a slightly larger wage impact of job opportunities for both men and women, consistent with the fact that they move when external offers are more productive. Nevertheless, the estimate for women is not statistically different from zero, and the impact is still substantially smaller than for men. Thus, women are unable to close the renegotiation gap by moving into higher-paying firms.

9 Conclusions

This study contributes to the growing literature on gender differences in labor market outcomes by highlighting the role of outside job opportunities in shaping the gender wage gap. Our findings indicate that while men's wages increase when exposed to outside job offers, women's wages remain largely unaffected. This discrepancy contributes significantly to the persistence of the gender pay gap, even within the same firm and occupation.

We developed a theoretical model that helps explain these gendered responses to outside offers. The model suggests that the difference in wage responses can be attributed to women's relative reluctance to engage in wage renegotiation when presented with outside job offers. While their wages are unaffected by external offers, they are almost as likely to switch employers, particularly when the new job offers higher wage premia or a shorter commute. This behavior

[47] Gallen and Wasserman 2021 finds no gender difference in network usage among undergraduates with access to alumni networks. Moreover, Table E1 shows that job opportunities linked to family ties are broadly as important whether they arise in the same occupation as the family tie or in a different one. This implies that family connections matter even when they do not involve working directly alongside the family member.

indicates that women perceive it costly to negotiate wage, which aligns with existing literature on gender differences in bargaining behavior.

Our results also reveal that women's job mobility is partly constrained by their job preferences, highlighting an additional factor contributing to the gender wage gap. Policies aimed at reducing these constraints could, therefore, play a crucial role in narrowing the gender pay gap. Furthermore, our findings suggest that initiatives encouraging women to renegotiate wages more assertively could help to mitigate within-firm gender wage disparities.

Our findings reflect the Swedish labor market, known for its relatively low wage dispersion and high gender equality. While these features likely matters for the absolute magnitude of the estimates we do not think that the share of the within spell growth in the gender wage gap that is due to renegotiation is necessarily contextual. We find that the gendered responses to outside offers can explain about half of the within-spell growth rate in the gender gap. We thus conjecture that this finding that is portable across contexts. With that said, it would of course be extremely valuable if future research could shed light on this conjecture.

In addition, while our results point to renegotiation aversion among women we cannot rule out that demand-side factors could play a role, such as employers being less likely to match outside offers for female workers or women shying away from renegotiation in anticipation of low returns. It should be noted that baseline job-to-job mobility is very similar for women and men suggesting that employers cannot exploit women's lower willingness to move in general. Additionally, the survey evidence provided by Caldwell et al. (2024) suggest that the primary reason for why women fail to bargain is disutility from asking rather than fear of backlash or expectations about lower pay-offs. Similarly, survey data in Biasi and Sarsons (2021) suggest that the gender negotiation gap among teachers is partly explained by gender differences in information and confidence. Future research could explore the mechanisms behind these gendered wage responses more deeply, particularly the role of employer practices and potential biases in wage-setting processes.

Finally, expanding the scope of analysis to include a wider range of social networks would provide a more comprehensive understanding of how outside options affect wage outcomes across different workers and contexts.

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Appendix A: Theory

The wage equation is given by

$$w(y, y_{-1}) = \beta y + (1-\beta)y_{-1} = w(y, b) + (1-\beta)(y_{-1} - b)$$

where y_{-1} denotes the next best offer. Our empirical work includes spell fixed effects and we thus focus on within-spell wage growth. The spell fixed effects control for y. Moreover, we take b as given. The unknown in the wage equation is y_{-1}.

Let $j = 0, 1, 2$ denote the number of wage updates the worker has received due to outside offers in our 3-period setting. Given a uniform distribution, the expected value of the next best offer, conditional on the number of wage updates, has an extremely simple form:

$$E(y_{-1}) = \begin{cases} b \text{ if } j = 0 \\ E(y' | \, y' < y, y, j = 1) = \frac{y+b}{2} \text{ if } j = 1 \\ E(y' | \, y' < y, y, j = 2) = \frac{1}{2}\left[y + \frac{y+b}{2}\right] \text{ if } j = 2 \end{cases}$$

In time period $t = 2$, the expected wage among stayers in a job with productivity y, is given by:

$$E(w_t | \, M, \lambda, y, y' < y) = w(y, b) + (1-\beta)\left\{E\left[y' \middle| \, y, y' < y, j = 1\right] - b\right\}\psi(M, \lambda, y, y' < y) \quad \text{(A1)}$$

where

$$\psi(M, \lambda, y, y' < y) = \left\{\Pr\left[j \geq 1 | \, M, \lambda, y, y' < y\right] + \frac{1}{2}\Pr\left[j = 2 | \, M, \lambda, y, y' < y\right]\right\} \quad \text{(A2)}$$

ψ measures how frequently the wage has been updated and is thus a measure of wage progression. Wage progression varies across individuals since they have been exposed to outside offers to different degrees. The action in this simple model essentially comes from ψ.

Let $F_t(y)$ denote the productivity distribution among those employed at the start of period t, and $F_{t-1}(y)$ the productivity distribution among those employed at the start of period $t-1$. Now, $F_t(y) = F_{t-1}(y)/\left[1 - F_{t-1}(b)\right]$. Let θ_{j-1} denote the share of workers renegotiating the wage, among the workers that stayed with the firm (with productivity y) conditional on the next best offer being y_{-1}. This share equals

$$\theta_{j-1}(M, y_{-1}) = \frac{\lambda_t(M)(F_t(y) - F_t(y_{-1}))}{1 - \lambda_t(M)(1 - F_t(y))}, \; j > 0 \quad \text{(A3)}$$

This says, for instance, that if $j = 1$, any outside offer between b and y will give rise to a renegotiated wage. If $j = 2$, there is within job wage dispersion, and the probability of renegotiation varies across individuals within job. Given a uniform distribution, we have

$$\theta_1(M) = E(\theta_1(M, y_{-1})) = \frac{\theta_0(M)}{2}.$$

Conditional on y_{-1}, the probability of getting j updates is given by

$$\Pr(j=0) = \left[1-\lambda_{t-1}(M)(1-F_{t-1}(b))\right](1-\theta_0)$$
$$\Pr(j=1) = \lambda_{t-1}(M)(1-F_{t-1}(b))(1-\theta_1) + \left[1-\lambda_{t-1}(M)(1-F_{t-1}(b))\right]\theta_0$$
$$\Pr(j=2) = \lambda_{t-1}(M)(1-F_{t-1}(b))\theta_1$$

where $\lambda_{t-1}(M)(1-F_{t-1}(b))$ is the probability of getting a wage update between periods 0 and 1 (either through renegotiation or mobility).

The probability of moving to another job is

$$\mu_t(M,y) = \lambda_t(M)\Pr(y'>y) = \lambda_t(M)(1-F_t(y)) \tag{A4}$$

A.1 Commuting aversion among women

We model commuting aversion as a reduction in the rate of acceptable offers. In particular we assume: $\lambda(M) = \lambda(1-d(1-M))$. For men all offers are thus acceptable: $\lambda(M=1)=\lambda$. While for women: $\lambda(M=0)=\lambda(1-d)$.

This assumption has a number of implications.

Result 1: Within-firm, women are paid less than men

Proof Define the within firm gender wage gap as $\Delta = E(w_t|\, M=0,\cdot) - E(w_t|\, M=1,\cdot)$. We have:

$$\Delta = (1-\beta)\left\{E\left[y'\middle|\, y, y'<y, j=1\right] - b\right\}\left[\psi(M=0,\cdot)-\psi(M=1,\cdot)\right] \tag{A5}$$

Since $E\left[y'|\, y, y'<y, j=1\right] > b$, $\psi(M=0,\cdot) < \psi(M=1,\cdot)$, implies $\Delta<0$. We have,

$$\psi(M=0,\cdot)-\psi(M=1,\cdot) = -d\lambda\left[1-F_{t-1}(b)\right]\left[\theta_1(M=1)+(1-\theta_0(M=0))\right] +$$
$$\left[\theta_0(M=0)-\theta_0(M=1)\right](1-\lambda(M=1)) + \left[\theta_1(M=0)-\theta_1(M=1)\right]\lambda(M=0)\left[1-F_{t-1}(b)\right]$$

The first term on the right-hand-side is negative. Also,

$$\frac{\partial\theta_0(M)}{\partial\lambda_t(M)} = \frac{\theta_0(M)}{\lambda_t(M)}\frac{1}{1-\lambda_t(M)(1-F_t(y))} > 0$$

Since $\theta_1(M) = \theta_0(M)/2$, $\frac{\partial\theta_0(M)}{\partial\lambda_t(M)} > 0$. Hence, $\theta_0(M=0) < \theta_0(M=1)$ and $\theta_1(M=0) < \theta_1(M=1)$. Thus, $\psi(M=0,\cdot) < \psi(M=1,\cdot)$, which implies $\Delta<0$.

Result 2: An outside offer (λ_t) has a smaller impact on women's wages than men's

Proof Differentiating (A5) with respect to λ_t we get

$$\frac{\partial\Delta}{\partial\lambda_t} = (1-\beta)\left\{E\left[y'\middle|\, y, y'<y, j=1\right]-b\right\}\left[\frac{\partial\psi(M=0,\cdot)}{\partial\lambda_t} - \frac{\partial\psi(M=1,\cdot)}{\partial\lambda_t}\right]$$

Since
$$\frac{\partial\psi(M=0,\cdot)}{\partial\lambda_t} - \frac{\partial\psi(M=1,\cdot)}{\partial\lambda_t} = (1-\lambda_{t-1}(1-F_{t-1}(b)))\left[\frac{\partial\theta_0(M=0)}{\partial\lambda_t} - \frac{\partial\theta_0(M=1)}{\partial\lambda_t}\right] + \lambda_{t-1}(1-F_{t-1}(b))\left[\frac{\partial\theta_1(M=0)}{\partial\lambda_t} - \frac{\partial\theta_1(M=1)}{\partial\lambda_t}\right] < 0$$

we have $\frac{\partial\Delta}{\partial\lambda_t} < 0$

Result 3: The impact of λ_t on job-to-job mobility is smaller among women than men

Proof From (A4) we obtain

$$\frac{\partial\mu_t(M=0,\cdot)}{\partial\lambda_t} - \frac{\partial\mu_t(M=1,\cdot)}{\partial\lambda_t} = -d(1-F_t(y)) < 0$$

A.2 Renegotiation aversion among women

Assume that renegotiation costs are so high that women do not renegotiate their wages with their current employer. They only negotiate their wages at the start of a new employment spell, and do not enter an alternating bargaining game with their previous employer. Thus, the wage in the previous match is the relevant outside option, when the wage in the new match is determined. Hence, the wage equation for women is given by

$$w(y,y_{-1}) = \beta y + (1-\beta)w_{-1} = w(y,b) + (1-\beta)(w_{-1}-b) = w(y,b) + (1-\beta)\beta(y_{-1}-b) \quad \text{(A6)}$$

where w_{-1} denotes the wage associated with the next best offer; with no relevant outside offers, $y_{-1} = b$.

Let w' denote the wage associated with an alternative offer. Women move to a new job whenever $w' > w$. Using (A6), this condition can be written as $\beta y' + (1-\beta)w > w$, or $y' > w$. We thus have that women move (stay) whenever the productivity associated with an offer is higher (lower) than the wage in the current match.

To focus on the essentials we ignore differential commuting aversion, and thus set $d = 0$, in this version of the model. As before, we are primarily interested in the wage among women (and men) that stayed in a job with productivity y.

Women either found this job in $t = 0$ or by moving to it between $t = 0$ and $t = 1$. Conditional on the productivity of the initial job, y_0, the probability of getting j wages updates for women is thus given by

$$\Pr(j=0) = 1-\lambda_{t-1}(1-F_{t-1}(w(y_0,b)))$$
$$\Pr(j=1) = \lambda_{t-1}(1-F_{t-1}(w(y_0,b)))$$
$$\Pr(j=2) = 0$$

The expected wage for women who stayed in a job with productivity y is given by

$$E(w|\, M=0,\lambda,y,y' < w(y,y_{-1}) = w(y,b) + (1-\beta)\beta\left\{E\left[y'|\, y, y' < w(y,y_{-1}), j=1\right] - b\right\}\tilde{\psi}(M=0,\cdot)$$

where

$$\tilde{\psi}(M=0,\lambda,y,y' < w(y,y_{-1})) = \Pr\left[j=1|\, y, y' < w(y,y_{-1}), \lambda\right]$$

Men behave as in the baseline model. Thus, equations (A1) and (A4) apply to them.

Result 4: The within-firm gender wage gap (Δ) is negative

Proof Δ can decomposed into

$$\Delta = (1-\beta)\left\{\underbrace{\left[\tilde{\psi}(M=0,\cdot)-\psi(M=1,\cdot)\right]}_{\text{(i) fewer wage adjustments}}\left[\bar{y}_s^{M=1}-b\right]+\underbrace{\left[\beta(\bar{y}_s^{M=0}-b)-(\bar{y}_s^{M=1}-b)\right]}_{\text{(ii) lower wage adjustments}}\tilde{\psi}(M=0,\cdot)\right\}$$

where $\bar{y}_s^{M=0} = E\left[y'|\, y, y' < w(y, y-1, j=1)\right]$ and $\bar{y}_s^{M=1} = E\left[y'|\, y, y' < y, j=1\right]$; by inspection, $\bar{y}_s^{M=0} < \bar{y}_s^{M=1}$. For individuals who stayed in a job of given productivity y, wages among women are lower for two reasons: (i) since women do not open renegotiation with their current employer, their wages have been adjusted on fewer occasions compared to men: $\tilde{\psi}^{M=0} < \psi^{M=1}$, and the first term in the decomposition is thus negative; (ii) when women locate a new employer, they use the wage with their current employer as the outside option in the negotiation; their outside option is thus lower than for men, who use the productivity associated with the outside option (men use the alternating bargaining game to extract all the surplus from the previous employer). The second term in the decomposition is also negative, and $\Delta < 0$.

Result 5: The gender wage gap (Δ) increases with λ_t

Proof Since, by assumption, the wage is not renegotiated for women, we have

$$\frac{\partial \Delta}{\partial \lambda_t} = -(1-\beta)\left\{\bar{y}_s^{M=1}-b\right\}\frac{\partial \psi(M=1,\cdot)}{\partial \lambda_t} < 0$$

Thus the (absolute value of the) gender wage gap increases in λ_t.

Result 6: The impact of λ_t on job-to-job mobility is greater among women than men

Proof Men move whenever the productivity associated with the offer is higher than the productivity associated with the current match: $\mu_t = \lambda_t(1-F_t(y))$. Women, on the other hand, move if the prospective employer can pay higher wages than the wage in the current match; that is, if $\tilde{\mu}_t(M=0,\cdot) = \lambda_t(1-F_t(\bar{w}(y))$, where $\bar{w}(y) = E\left[w(y,\cdot))\right]$ denotes the average wage among women in a job with productivity y. We have

$$\frac{\partial \tilde{\mu}_t(M=0,\cdot)}{\partial \lambda_t} - \frac{\partial \mu_t(M=1,\cdot)}{\partial \lambda_t} = F_t(y) - F_t(\bar{w}(y)) > 0$$

which is positive since $\bar{w}(y) < y$.

Appendix B: Compensating differentials for distance

Our results suggest that women do not use outside offers to renegotiate wages. However, they move in response to outside offers; thus, we use the mobility responses to estimate compensating differentials for distance by gender.

In particular, we ask the following question: How much extra productivity do individuals require in order to move to a job which is further away from their current place of residence? To answer this question, let y denote the productivity associated with outside job offer and D the distance to this offer. The utility associated with the outside offer is thus $U(y, D)$. The productivity/distance combination that holds utility constant – i.e., the compensating differential for distance – is thus given by

$$\frac{\partial y}{\partial D} = -\frac{U_D}{U_y}$$

To estimate this compensating differential by gender, we use the mobility estimates reported in Table C5. In practice, we thus calculate

$$\text{compensating differential} = -\frac{\partial\mu/\partial D_{\text{long}} - \partial\mu/\partial D_{\text{short}}}{\partial\mu/\partial y_{\text{high}} - \partial\mu/\partial y_{\text{low}}} \tag{B1}$$

where μ denotes mobility, D_{long} (D_{short}) a long (short) commute, and y_{high} (y_{low}) high (low) productivity; we approximate high/low productivity using estimated AKM firm wage premia.

For women, we obtain

$$\text{compensating differential}_{\text{women}} = -\frac{0.076 - 0.320}{0.720 - 0.220} = 0.488 \text{ (SE: 0.060)}$$

while for men

$$\text{compensating differential}_{\text{men}} = -\frac{0.082 - 0.270}{0.940 - 0.250} = 0.272 \text{ (SE: 0.034)}$$

The compensating differential for distance is thus almost twice as large for women compared with men. The difference between women and men is statistically significant at the 5 % level (standard errors are calcualted using the delta method).

Appendix C: Additional results

Table C1: Gender Wage Gap

	Regression sample			All private sectore workers in WSS		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	White Collar	Blue Collar	All	White Collar	Blue Collar
Raw	-0.11	-0.16	-0.080	-0.11	-0.17	-0.082
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Within occupation	-0.082	-0.100	-0.039	-0.082	-0.10	-0.039
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Within establishment	-0.099	-0.14	-0.036	-0.10	-0.14	-0.035
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Within establishment-occupation	-0.067	-0.084	-0.027	-0.067	-0.086	-0.026
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	7631964	4623474	3008490	10777541	6501253	4276288

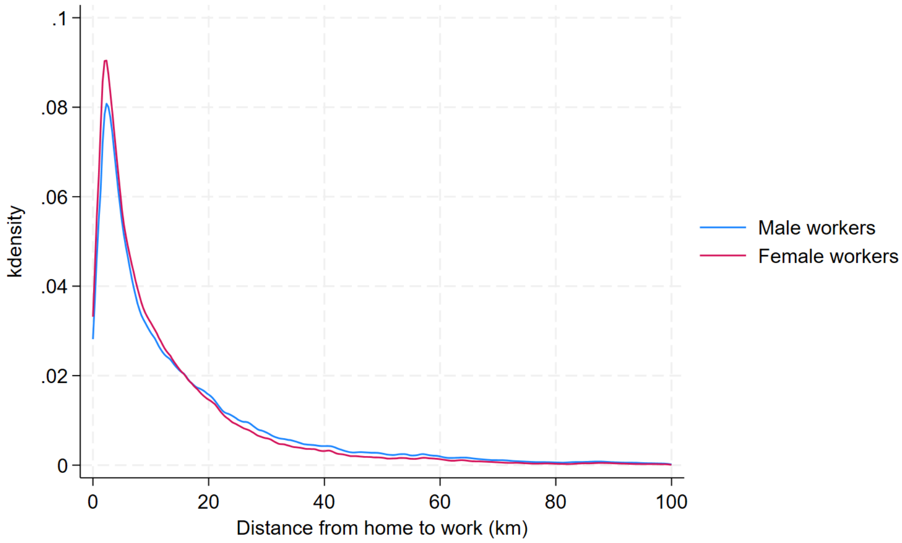
Note: The table shows the estimated coefficient on an indicator for being a woman in individual-level wage regressions with log hourly wage as the dependent variable. All regressions include age, education and year dummies. Occupations are measured at the three digit level. Columns headed "All private sector workers in WSS" use all observations available in the WSS data, while columns headed "Regression sample" shows estimates for the sample used in the empirical analysis. The main difference between the two samples is that the latter sample conditions on workers having at least one employed family link.

Table C2: Gender Mobility Gap

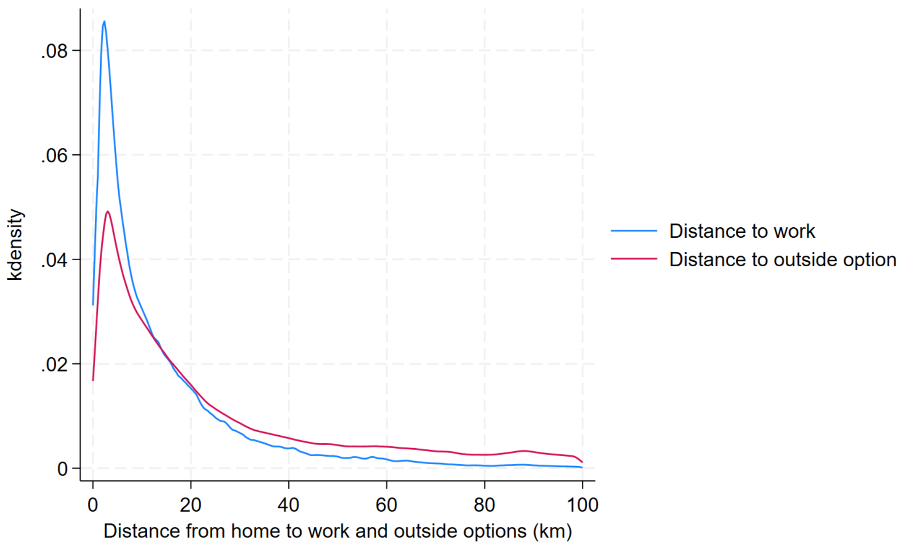
	Regression sample			All private sectore workers in WSS		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	White Collar	Blue Collar	All	White Collar	Blue Collar
Raw	0.0080	0.0023	0.0053	0.0079	0.0030	0.0042
	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)
Within occupation	-0.0042	-0.0021	-0.0088	-0.0038	-0.0015	-0.0088
	(0.0003)	(0.0003)	(0.0004)	(0.0002)	(0.0003)	(0.0003)
Within establishment	-0.0051	-0.0058	-0.0077	-0.0044	-0.0052	-0.0074
	(0.0002)	(0.0003)	(0.0004)	(0.0002)	(0.0002)	(0.0003)
Within establishment-occupation	-0.0059	-0.0059	-0.0068	-0.0051	-0.0049	-0.0064
	(0.0003)	(0.0004)	(0.0004)	(0.0002)	(0.0003)	(0.0003)
Observations	7631964	4623474	3008490	10777541	6501253	4276288
Mean dep. variable	.0978	.1122	.0756	.0934	.1075	.0718

Note: The table shows the estimated coefficient on an indicator for switching employer between two consecutive years using the same samples and specifications as for wages, described in the table to Table C1.

Figure C1: Distance to work and outside options



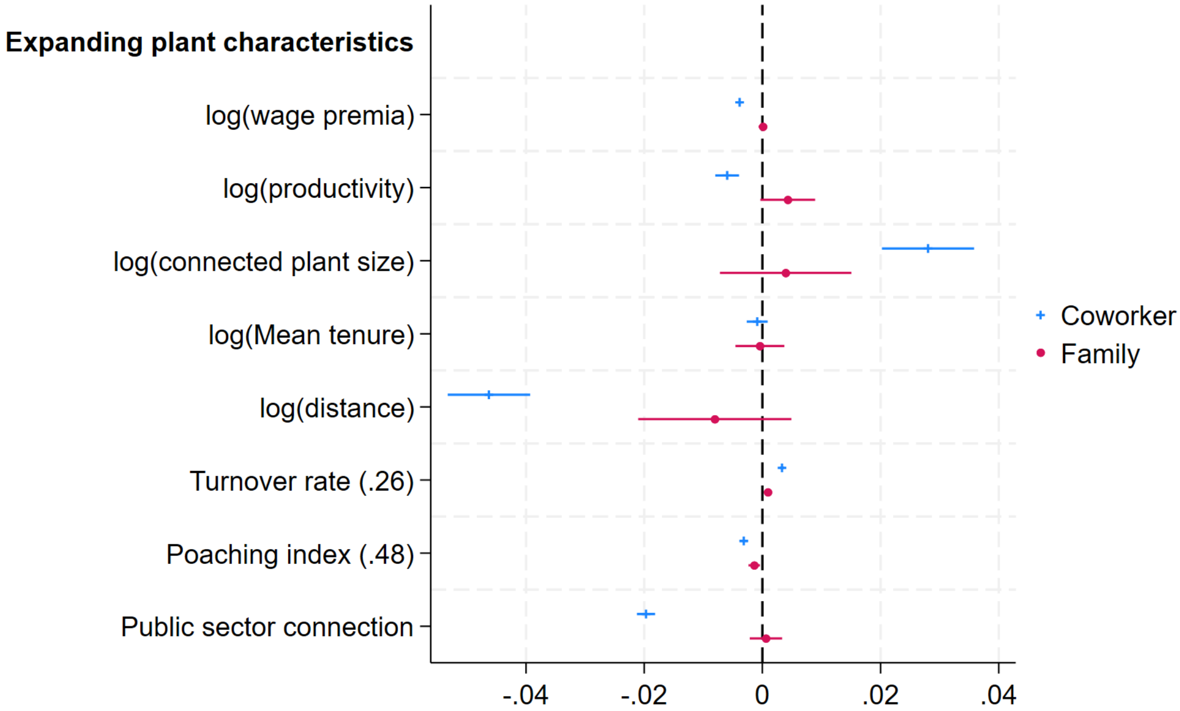
(a) Distance to Work by Gender



(b) Distance to Work vs Outside Option

Notes: The Figure in Panel (a) shows distance to work distributions by gender for private sector white collar workers. Panel (b) shows distance to current workplace and distance to the connected plant of all workers.

Figure C2: Gender balance in the quality of job openings: family vs. coworker networks



Note: The figure shows estimates on an indicator for being a woman, in separate regressions where row headings correspond to the dependent variable. The regression specification includes flexible controls for age, education, establishment x year, and occupation x year fixed effects. The sample is restricted to white-collar workers and corresponds to the sample in Column (1) of Table 2. Where relevant, mean of dependent variables are reported within parentheses. The red dots are the same as in Figure 2 while the blue dots show the corresponding estimates for coworker networks.

Table C3: Summary Statistics of Blue Collar Sample

	All workers	Male workers	Female workers
	(1)	(2)	(3)
Panel A. Age and Education			
Age	40.7	40.7	40.8
Compulsory or less	0.18	0.18	0.17
High school	0.73	0.74	0.73
College	0.087	0.081	0.10
Panel B. Wages and separations			
Log hourly wage	5.10	5.12	5.04
Within-job wage growth	0.020	0.020	0.020
SD(Within-job wage)	0.081	0.082	0.075
Var(Within-job wage growth)	0.0095	0.0099	0.0082
Separation	0.13	0.11	0.18
Separation to any plant	0.076	0.073	0.082
Separation to non-employment	0.052	0.038	0.093
Panel C. Occupations			
Service workers and shop sales workers	0.20	0.11	0.44
Skilled agricultural and fishery workers	0.011	0.011	0.013
Craft and related trades workers	0.23	0.29	0.059
Plant machine operators and assemblers	0.37	0.41	0.26
Elementary occupations	0.095	0.084	0.13
Panel D. Family links			
Number of family links	4.46	4.44	4.50
Number of employed family links	1.98	1.97	2.00
Number of employed parents	0.51	0.52	0.51
Number of employed siblings	1.47	1.46	1.49
Share of males in network	0.54	0.54	0.53
Panel E. Outside opportunities			
Number of outside opportunities (Ω_{it})	116.6	115.0	121.0
Number of outside opportunities in own occupation (Ω_{iot})	7.30	6.80	8.74
At least one outside opportunity in own occupation (OO_{iot})	0.49	0.49	0.49
OO in parents' plant	0.14	0.14	0.14
OO in siblings' plant	0.40	0.40	0.40
Panel F. Establishments			
Plant size	40.8	49.7	28.8
Distance: home to current plant (km)	16.0	16.8	13.7
	(7.54)	(8.04)	(6.36)
Distance: home to connected plant (km)	80.1	79.1	83.2
	(22.0)	(21.6)	(23.4)
Observations	2995332	2220632	774700

Note: The table replicates Table 2 for blue collar workers. Medians are reported in paranthesis for distance to current plant and distance to connected plant.

Table C4: Wage Effects - Heterogeneity by characteristics of the offer

Panel A: OO by Plant Wage Premia	Males	Females
OO in higher wage premia plant	0.080***	0.035
	(0.028)	(0.029)
OO in lower wage premia plant	0.049**	-0.038
	(0.020)	(0.024)
Observations	2405671	1558234
Adjusted R^2	0.950	0.956
p-value for gender difference		.264
Panel B: OO by Sector	Males	Females
OO in private sector	0.062***	-0.0044
	(0.020)	(0.023)
OO in public sector	0.033	-0.047
	(0.028)	(0.031)
Observations	2405671	1558234
Adjusted R^2	0.950	0.956
p-value for gender difference		.031
Panel C: OO by Commuting Distance	Males	Females
OO with shorter commute	0.049*	0.023
	(0.026)	(0.030)
OO with longer commute	0.040**	-0.024
	(0.020)	(0.022)
Observations	2405671	1558234
Adjusted R^2	0.950	0.956
p-value for gender difference		.517
Panel D: OO by Local Labor Market	Males	Females
OO in the same local labor market	0.051**	0.0095
	(0.023)	(0.025)
OO in other local labor markets	0.045*	-0.017
	(0.024)	(0.029)
Observations	2405671	1558234
Adjusted R^2	0.950	0.956
p-value for gender difference		.22
Worker x Plant FE	Yes	Yes
Plant x Year FE	Yes	Yes
Occ x Year FE	Yes	Yes
Age FE	Yes	Yes

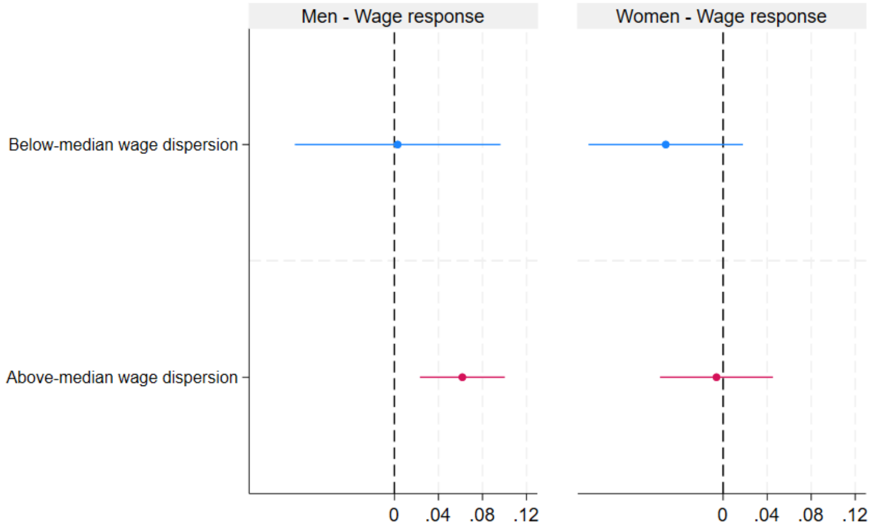
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table shows estimates of β^A and β^B from the models $log(wage)_{ijt} = \beta^A \text{OO}^A_{iot} + \beta^B \text{OO}^B_{iot} + \alpha_{ij} + \alpha_{jt} + \alpha_{ot} + X'_{it}\delta + \epsilon_{ijt}$, where we distinguish outside opportunities (OO^A_{iot} and OO^B_{iot}) based on whether they originate from higher-/lower-productivity plants (Panel A.), private/public sector (Panel B.), shorter/longer-commute plants (Panel C.), and same/different local labor markets (Panel D.). We run this model separately for men and women. Standard errors are clustered at the plant x occupation x year level. Coefficients are multiplied by 100.

Table C5: MOBILITY EFFECTS - HETEROGENEITY BY CHARACTERISTICS OF THE OFFER

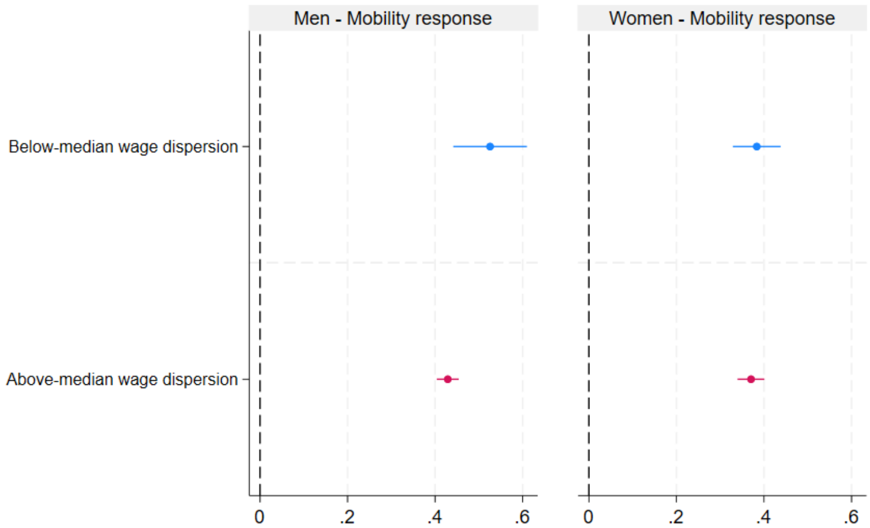
Panel A: OO by Plant Wage Premia	Males	Females
OO in higher wage premia plant	0.94***	0.72***
	(0.031)	(0.028)
OO in lower wage premia plant	0.25***	0.22***
	(0.012)	(0.014)
Observations	2405671	1558234
Adjusted R^2	0.089	0.097
p-value for gender difference		0
Mean dep. variable	.001	.001
Panel B: OO by Sector	Males	Females
OO in private sector	0.58***	0.50***
	(0.015)	(0.017)
OO in public sector	0.030***	0.048***
	(0.0100)	(0.012)
Observations	2405671	1558234
Adjusted R^2	0.088	0.095
p-value for gender difference		0
Mean dep. variable	.001	.001
Panel C: OO by Commuting Distance	Males	Females
OO with shorter commute	0.27***	0.32***
	(0.019)	(0.023)
OO with longer commute	0.082***	0.076***
	(0.011)	(0.013)
Observations	2405671	1558234
Adjusted R^2	0.085	0.093
p-value for gender difference		.155
Mean dep. variable	.001	.001
Panel D: OO by Local Labor Market	Males	Females
OO in the same local labor market	0.65***	0.55***
	(0.018)	(0.019)
OO in other local labor markets	0.15***	0.10***
	(0.011)	(0.012)
Observations	2405671	1558234
Adjusted R^2	0.088	0.096
p-value for gender difference		0
Mean dep. variable	.001	.001
Worker x Plant FE	Yes	Yes
Plant x Year FE	Yes	Yes
Occ x Year FE	Yes	Yes
Age FE	Yes	Yes

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table shows estimates of β^A and β^B from the models $\mathbf{1}(\text{Mobility to Connected Plant})_{ijt} = \beta^A \text{OO}^A_{iot} + \beta^B \text{OO}^B_{iot} + \alpha_{ij} + \alpha_{jt} + \alpha_{ot} + X'_{it}\delta + \epsilon_{ijt}$, where we distinguish outside opportunities (OO^A_{iot} and OO^B_{iot}) based on whether they originate from higher-/lower-productivity plants (Panel A.), private/public sector (Panel B.), shorter/longer-commute plants (Panel C.), and same/different local labor markets (Panel D.). We run this model separately for men and women. Standard errors are clustered at the plant x occupation x year level. Coefficients are multiplied by 100.

Figure C3: High vs. Low Wage Dispersion Occupations



(a) WAGES



(b) MOBILITY

Note: This figure shows log hourly wages (Panel a.) and mobility to connected plant (Panel b.) in response to OO_{iot} in high vs. low wage dispersion occupations. We use the full sample of white-collar workers in the private sector and calculate the average standard deviation of log wages for each occupation over the sample period. Occupations are then categorized into two groups based on a median split of this measure. We then run the main regressions separately for occupations with above-median and below-median wage dispersion, and for each gender. Standard errors are clustered at the plant x occupation x year level. Coefficients are multiplied by 100.

Appendix D: Robustness checks

Table D1: Robustness checks for wages

Dep. var: Log hourly wage	Males	Females
Panel A: Weighted by share men/women in occupation		
OO_{iot}	0.056***	-0.013
	(0.018)	(0.028)
Observations	2405671	1558215
Adjusted R^2	0.950	0.959
p-value for gender difference		.038
Panel B: Net instead of gross expansions		
OO_{iot}	0.049***	0.00043
	(0.017)	(0.020)
Observations	2405671	1558234
Adjusted R^2	0.950	0.956
p-value for gender difference		.061
Panel C: Outside options (linear)		
Ω_{iot}	0.00099***	0.00041
	(0.00027)	(0.00032)
Observations	2405671	1558234
Adjusted R^2	0.950	0.956
p-value for gender difference		.165
Panel D: Plant x Occ x Year FEs		
OO_{iot}	0.067***	-0.0077
	(0.019)	(0.023)
Observations	2136637	1298905
Adjusted R^2	0.951	0.957
p-value for gender difference		.011
Panel E: Relaxing occupation restriction		
OO_{iot}	0.038**	-0.018
	(0.019)	(0.020)
Observations	2405671	1558234
Adjusted R^2	0.950	0.956
p-value for gender difference		.04
Worker x Plant FE	Yes	Yes
Plant x Year FE	Yes	Yes
Occ x Year FE	Yes	Yes
Age FE	Yes	Yes

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table shows estimates of log hourly wages in response to OO_{iot}. We report estimates in columns 1 and 2 separately for men and women. Corresponding p-values for the difference are shown under each panel. Standard errors are clustered at the job (plant x occupation x year) level. In Panel A. we re-weight the gender-specific regressions so that the distribution of men and women are the same across occupations. In practice, we give each observation in the female regression the weight $w_{fot} = \#Men_{ot}/\#Women_{ot}$, where o denotes occupation. In Panel B., we use the net expansions instead of gross expansions as a measure of OO_{iot}. In Panel C. we use total number of gross expansions (Ω_{iot}) as the main variable of interest. In Panel D., we use a broader level of our occupational proxy- the 2-digit (25 categories) instead of 3-digit (116 categories) level of the Swedish education code (SUN)- to relax the occupation restriction in measuring relevant job openings in all connected firms.

Table D2: Robustness checks for mobility

Dep. var: Log hourly wage	Males	Females
Panel A: Weighted by share men/women in occupation		
OO_{iot}	0.45***	0.44***
	(0.013)	(0.022)
Observations	2405671	1558215
Adjusted R^2	0.087	0.150
p-value for gender difference		.548
Panel B: Net instead of gross expansions		
OO_{iot}	0.40***	0.35***
	(0.011)	(0.013)
Observations	2405671	1558234
Adjusted R^2	0.087	0.094
p-value for gender difference		.003
Panel C: Outside options (linear)		
Ω_{iot}	0.0044***	0.0037***
	(0.00041)	(0.00039)
Observations	2405671	1558234
Adjusted R^2	0.086	0.094
p-value for gender difference		.221
Panel D: Plant x Occ x Year FEs		
OO_{iot}	0.47***	0.40***
	(0.014)	(0.015)
Observations	2136637	1298905
Adjusted R^2	0.053	0.047
p-value for gender difference		0
Panel E: Relaxing occupation restriction		
OO_{iot}	0.36***	0.28***
	(0.011)	(0.011)
Observations	2405671	1558234
Adjusted R^2	0.086	0.094
p-value for gender difference		0
Worker x Plant FE	Yes	Yes
Plant x Year FE	Yes	Yes
Occ x Year FE	Yes	Yes
Age FE	Yes	Yes

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table shows estimates of mobility to connected plants in response to OO_{iot}. We report estimates in columns 1 and 2 separately for men and women. Corresponding p-values for the difference are shown under each panel. Standard errors are clustered at the job (plant x occupation x year) level. In Panel A. we re-weight the gender-specific regressions so that the distribution of men and women are the same across occupations. In practice, we give each observation in the female regression the weight $w_{fot} = \#Men_{ot}/\#Women_{ot}$, where o denotes occupation. Panel B. uses the net expansions instead of gross expansions as a measure of OO_{iot}. Panel C. uses total number of gross expansions (Ω_{iot}) as the main variable of interest. In Panel D., we use a broader level of our occupational proxy- the 2-digit (25 categories) instead of 3-digit (116 categories) level of the Swedish education code (SUN)- to relax the occupation restriction in measuring relevant job openings in all connected firms.

Appendix E: Results on alternative mechanisms

Table E1: Wage and Mobility Responses by Connection's Occupation

	Males	Females
Panel A: Log hourly wage		
OO_{iot} - link is in the same occupation	0.060	0.026
	(0.044)	(0.049)
OO_{iot} - link is in another occupation	0.042**	-0.023
	(0.019)	(0.022)
Observations	2405671	1558234
Adjusted R^2	0.950	0.956
	Males	Females
Panel B: Mobility to connected plant		
OO_{iot} - link is in the same occupation	0.70***	0.52***
	(0.035)	(0.037)
OO_{iot} - link is in another occupation	0.41***	0.35***
	(0.012)	(0.014)
Observations	2405671	1558234
Adjusted R^2	0.087	0.095
Worker FE	Yes	Yes
Plant x Year FE	Yes	Yes
Occ x Year FE	Yes	Yes
Age FE	Yes	Yes

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table shows estimates of β^A and β^B from the models $Y_{ijt} = \beta^A \text{OO}^A_{iot} + \beta^B \text{OO}^B_{iot} + \alpha_{ij} + \alpha_{jt} + \alpha_{ot} + X'_{it}\delta + \epsilon_{ijt}$, where we distinguish outside opportunities (OO^A_{iot} and OO^B_{iot}) based on whether the family connection's occupation is the same as the focal person's. We run this model separately for men and women. Standard errors are clustered at the plant x occupation x year level. Coefficients are multiplied by 100.

Table E2: Labor earnings responses

	Baseline		Conditional on earnings at t-1	
	(1)	(2)	(3)	(4)
	Males	Females	Males	Females
OO_{iot}	0.071***	0.041	0.065**	0.038
	(0.027)	(0.039)	(0.027)	(0.038)
Monthly Earnings$_{it-1}$			15.9***	18.5***
			(0.18)	(0.19)
Observations	2405671	1558234	2405671	1558234
Adjusted R^2	0.903	0.879	0.906	0.885
p-value for gender difference		.525		.56
Mean dep. variable	10.596	10.378	10.596	10.378
Worker x Plant FE	Yes	Yes	Yes	Yes
Plant x Year FE	Yes	Yes	Yes	Yes
Occ x Year FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes

Note: This table shows estimates log monthly earnings in response to OO from the main estimating equation separately for men and women: 13: $Y_{ijt} = \beta OO_{iot} + \alpha_{ij} + \alpha_{jt} + \alpha_{ot} + X'_{it}\delta + \epsilon_{ijt}$. Columns 2 and 4 control for the log of monthly earnings in the previous year. Standard errors are clustered at the plant x occupation x year level.

Table E3: Hours worked response

Dependent variable: Hours Worked	(1)	(2)
	Males	Females
OO_{iot}	0.032	0.10
	(0.060)	(0.078)
Observations	2405650	1558204
Adjusted R^2	0.411	0.436
Mean dep. variable	151.389	144.966
Worker x Plant FE	Yes	Yes
Plant x Year FE	Yes	Yes
Occ x Year FE	Yes	Yes
Age FE	Yes	Yes

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table shows estimates of hours worked in response to OO from the main estimating equation separately for men and women: 13: $Y_{ijt} = \beta OO_{iot} + \alpha_{ij} + \alpha_{jt} + \alpha_{ot} + X'_{it}\delta + \epsilon_{ijt}$. Hours worked refer to monthly contracted working hours. Standard errors are clustered at the plant x occupation x year level. Coefficients are multiplied by 100.

Table E4: Worker FE instead of Spell FE

	Males	Females
Panel A: Log hourly wage		
OO_{iot}	0.077***	0.032
	(0.019)	(0.022)
Observations	2548904	1671536
Adjusted R^2	0.938	0.944
p-value for gender difference		.133
Mean dep. variable	5.48	5.322

	Males	Females
Panel B: Mobility to connected plant		
OO_{iot}	0.41***	0.36***
	(0.011)	(0.012)
Observations	2548904	1671536
Adjusted R^2	0.066	0.077
p-value for gender difference		.003
Mean dep. variable	.001	.001
Worker FE	Yes	Yes
Plant x Year FE	Yes	Yes
Occ x Year FE	Yes	Yes
Age FE	Yes	Yes

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table shows estimates log hourly wages (Panel A.) and mobility to connected plants (Panel B.) in response to OO from the estimating equation separately for men and women: 13: $Y_{ijt} = \beta OO_{iot} + \alpha_i + \alpha_{jt} + \alpha_{ot} + X'_{it}\delta + \epsilon_{ijt}$. The only difference from the main specification is we replace spell fixed effect (α_{ij}) by worker fixed effects (α_i). We report estimates of β_1 (in columns 1 and 2) separately for men and women, and p-value for the gender difference from the full sample. Standard errors are clustered at the plant x occupation x year level. Coefficients are multiplied by 100.